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A Simulation Study of Centralized versus Decentralized Healthcare Admission Processes

Jacob Smyth
jbs6893@rit.edu

A Simulation Study of Centralized versus Decentralized Healthcare Admission Processes

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Approved by:

Dr. Michael E. Kuhl, Thesis Advisor

Dr. Nazibeh Azadeh Fard

Abstract

With an expanding number of healthcare clinics and a growing trend of consolidation, the possibility of a centralized location performing admission for multiple clinics has been presented as a possible method to save on operational costs. This centralized approach would cause significant changes in the admission process for decentralized clinics that have their own admission processes, and the effect on quality of care cannot be ignored when deciding which method to use. To determine the characteristics under which a centralized or decentralized admission system would be better, a discrete event simulation methodology is designed and utilized to compare the alternative approaches. Using the model and real-world data, a better understanding of the criteria that works best for each system can be gained and used as a guide for clinical organizations considering this choice. An experimental performance evaluation investigates factors including arrival rate per day, the mixture of patients for each clinic, the percentage of patients who have multiple appointments, the travel time to clinics, and the number of clinics in each system. Overall these experiments reveal that a centralized system can obtain the same or faster wait times than the decentralized system with less staffing in certain scenarios such as an increase in the number of clinics and number of multiple appointment patients. However, the centralized system with fewer staff can result in slightly higher maximum wait times than the decentralized model. A validation case study, supports the results and demonstrates the usefulness of the simulation methodology.

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1 Introduction

The healthcare system in the United States currently is one of the costliest in the world with 3.5 trillion dollars being spent on healthcare in 2017, an average cost of $11,000 per person (Centers for Medicare and Medicaid Services, 2019). This accounts for approximately eighteen percent of the total GDP of the United States and a future projection made by the Center for Medicare and Medicaid Services states that further growth in cost can be expected. According to predictions, by 2027 the US will spend 6 trillion dollars on healthcare, an increase of 2.5 trillion (or roughly 70%) over the course of ten years. This will become 19% of the total GDP and would cost the average American adult $17,000 per year (Centers for Medicare and Medicaid 3 Services, 2019). Another clear sign of the growth in the healthcare industry is the increasing number of Medical School Graduates. Over just the ten years between 2008 and 2018, the number of medical school graduates went from roughly sixteen thousand to almost twenty-six thousand (Culler, 2013). Not only has the number of Medical professionals increased greatly, but research has also found that there is now a greater percentage who are salaried professionals working in a clinical setting instead of having their own private practice (Kane, 2013). It is primarily job security and greater pay that is driving doctors to make this switch, as a growing percentage of Americans going to clinics instead of private practices. While data for this thesis primarily focuses on America, the results should be able to be applied globally wherever conditions are similar.

As this shift has occurred, primary care doctor visits have declined by eighteen percent between 2012 and 2016 (Health Care Cost Institute, 2018), while visits to specialists increased during that time. This has created opportunities for clinics, which can prioritize on faster service for incoming patients and can also be specialized. This is seen with the steady increase in outpatient care over the past three decades while around thirty percent of hospitals have negative operating margins (American Hospital Association, 2018). This would indicate that clinics may perform better financially than both larger hospitals and small private practices. Both Urgent Care Clinics and Retail Clinics have greatly expanded in usage, with Urgent Care centers increasing from 6,100 locations in 2013 to 8,774 in 2018 (Urgent Care Association, 2018). As clinics are increasing both in number and importance to the healthcare system of the United States, efforts to improve clinical efficiency would have both large financial impacts and qualitative impacts on how a large section of Americans are treated.

These changes in the structure of the healthcare industry have also led to the increasing trend of consolidation of clinics. Slightly over a quarter of healthcare leaders polled believed consolidation to be the most important trend (Definitive Healthcare, 2019). Larger corporations such as CVS and Walmart are becoming involved in this trend due to a variety of financial reasons. Research into centralized healthcare organizations shows more positive results both financial assets and quality of care over decentralized clinics (Audi, 2014). These mergers not only can provide the clinics with more capital backing them, but can also result in consolidation of separate departments across multiple clinics (Bazzoli, 2002). In more urban settings the increase in clinics and mergers has led to the possibility of consolidating the physical spaces as well. These mergers not only can impact the physical layouts of these combined clinics but can also impact the processes as well, in particular the admission process.

Admission is a key area in customer satisfaction is the waiting time of their visit (Mohebbifar, 2013). While consolidation may decrease costs in admission, any increases in waiting time that may occur would damage customer opinion. Therefore, there is a difficult balance between reducing administrative and operational costs while maintaining the best level of customer satisfaction possible. Another focus of attention on the effect of mergers on admission is the continuity of care. Handoff of patients between medical professionals become more prevalent due to these mergers, and research on common handoff tools and techniques show a wide variety in terms of quality and rigor (Abraham, 2014). As there is a multitude of tools and techniques, the likelihood of clinics being merged together having different admission and handoff processes is high. There has been research into the most effective methods of handing off patients to reduce information loss (Collins, 2012), which can hopefully reduce the risk of increasing errors due to centralization. These most recent handoff tools are generally electronic and attempt to capture customer satisfaction metrics.

The scope of this thesis will examine both the operational and qualitative differences between the centralized and decentralized healthcare admission processes for a group of clinics, including factors such as wait time that has a significant impact on customer satisfaction. A Discrete Event Simulation (DES) modeling methodology designed and developed to evaluate alternative admission systems. The simulation modeling will be modular to enable use across many different settings that vary the arrival rate, the number of clinics, and the processes being conducted at each clinic so that a greater understanding of the conditions that favor each system can be gained.

To validate the methodology, data from a large healthcare organization with multiple closely located clinic facilities will be examined.

2 Problem Statement

There are many specialized healthcare clinics in the United States, due to financial or administrative reasons are usually located near other healthcare clinics owned by the same organization. There are many different reasons for healthcare organizations to do this as there are many benefits that can be gained from locating multiple clinics nearby or in the same facility. With clinics being close together, there is greater freedom in looking for methods to reduce administrative inefficiencies or find cost saving measures. Due to the high administrative costs associated with healthcare that accounts for 8% of the total healthcare costs in the U.S. (greater than the world average of 2%, Tseng, 2018), one possible area for improvement that has been considered is the admission process. Healthcare clinics often have their own admission process and desk associated with that clinic, but the clustering of clinics has created the opportunity for one admission desk to cover admissions for multiple clinics. This could be beneficial in reducing administrative costs for the healthcare organization that has multiple clinics in the same area, but could also increase travel times and delays for incoming patients. Determining the conditions in which a centralized system would perform better than a decentralized system could potentially deliver large savings and possible space savings for the organization. Likewise, determining the conditions that best suit a decentralized system would help organizations decide on a method that does not sacrifice quality of care. By using discrete event simulation, we can evaluate the criteria and performance for each system alternative without having to implement these changes in the real-world which could be costly, time consuming, and harmful to patient satisfaction.

The first objective of this thesis is to design a simulation modeling methodology for the evaluation of decentralized versus centralized healthcare clinic admission processes. In particular, the methodology will be designed to enable healthcare clinics to compare the operational costs and benefits of each alternative. Furthermore, the methodology will be designed to study the factors that influence the performance of decentralized versus centralized clinic admission processes and under which conditions one alternative may be preferred over the other.

The second objective is to construct a simulation model (or models) that includes the significant parameters for a comparison between a decentralized and a centralized system. This model will incorporate key metrics that reflect on both operational efficiency and savings as well as customer satisfaction. The model will be flexible to try different scenarios to test different criteria and their effect on the two systems.

The third objective is to validate the model using real-world data from a group of clinics at Roswell Park Cancer Institute, and determine which system would better fit their needs. Several different scenarios will be tested on their clinics to determine if full centralization or decentralization is the best choice, or if a mixture of the two models will provide the best balance between operational gains and customer satisfaction. This case study will help to validate the results and findings for the set of general experiments for healthcare clinics described previously.

The final objective is to gain a more general view of the conditions in which each system performs better than the other. This set of criteria will hopefully be a useful guide to organizations considering the consolidation of multiple clinics even if they do not have a DES model to help with their decision making.

The completion of this simulation study is intended to serve as a methodology and framework that can be used to help other healthcare organizations decide between a centralized and a decentralized system for their healthcare clinics.

3 Literature Review

3.1 General Healthcare Simulation

DES is a popular and agile tool that works well with the restrictions of the healthcare industry (Mustafee, 2010). When considering alterations or expansions to a healthcare facility, DES can show the effects without any dangers of implementing these changes in real life. While these simulations can be useful for a wide arrange of issues that clinics face, this thesis is solely focused on the admission process of clinics. Most simulations will have incoming patients be of a single entity type, so they should be treated somewhat similarly. However, aspects such as whether or not the patient has insurance or if they are a first-time patient can affect the admission process. These distinctions are not always significant enough to warrant being incorporated into the model, and the time difference between these groups may be captured in the general distribution for the interarrival time of patients.

Clinical admission is typically centered around three main activities; registration, consultation, and examination (Bhattacharjee, 2014), though not all patients go through every step in the admission process. There may also be differences in patient flow depending on patient type (Faddy, 2005). This is a multi-step process that involves a variety of resources/workers to operate from the clinic's point of view (Hulshof, 2012). Often each activity in admission has multiple subtasks with their own staff and room requirements, a patient routing is affected by the availability of these resources (Ceresoli, 2019). The length of Admission times does depend on what the clinic considers as part of their admission process as compared to their test or treatment process. Therefore, the number of steps changes for each paper, but the organization of these steps is following a similar process flow that involved the separation of the steps that the patient performs and the steps that are performed by the staff, along with the location each step is performed and whether they are sequential or can be done concurrently (Granja, 2014). Once all of these process steps are gathered it is important to examine the type of clinic as while many processes are the same, the key measurements of success do vary by clinic type.

3.2 Clinical Admission Simulation

Admission Processes generally depend on the type of clinic, but the technology being used can impact both the processes and the time associated with admission. These technological changes can take place independently of the appointment strategy of the clinic. While there are many approaches to incorporating technology to assist admission, the most common form is an admission kiosk (Clinic, 2012).

3.2.1 Walk in Clinical Admission

There are many distinctions that can be made between healthcare clinics, yet the most significant factor for determining both admission processes and how to quantify quality of care is whether a clinic is appointment only, walk in, or both. Walk in clinics are hard to manage and staff for due to the higher uncertainty than more appointment-oriented clinics, yet they have a large appeal for patients who have difficulties in setting a time for an appointment or have urgent care needs, and for managers who are frustrated at late arrivals and no shows. Research into walk in clinics have generally focused around admission strategies to deal with the high uncertainty of these clinics. Generally, a walk-in clinic has two medical assistants and one physician on staff at all times, and a more uneven amount of arrivals throughout the day is a reasonable assumption for walk in clinics. Medical Assistants is a broad category that can refer to nurses, clinical assistants, or another occupation that is primarily focused on more routine tasks that are necessary to operate a clinic. Patients who arrived had six steps in their admission process, two of which were waiting, as they made their way from the waiting room to the assessment room, and finally to an examination room (Reese, 2017).

3.2.2 Appointment-Based Clinical Admission

No shows and late arrivals are a likely occurrence for appointment-based clinic, with a clinical no-show rate of around 6% of all appointments being a reasonable assumption, even for specialized clinics (Santibáñez, 2009). Even with what would seem like a small rate of no-shows, the effect of these missed appointments led to a less efficient than planned patient flow. Adding to this problem, appointment-based clinics have to deal with a greater level of customer dissatisfaction as there is a time associated with their appointments, whereas patients entering a walk-in do not have a clear time associated with when they think they will be admitted. Therefore, if a patients' appointment is delayed it can lead to both lesser customer experience and also create further problems with the patient flow for the clinic. While the steps for admission are remarkably similar to Figure 1, the main difference is the effect the appointments have on scheduled appointments and the importance of meeting the appointment time plays on quality of care. From a patient perspective there are three major types of delay in an appointment-based system; Type I delays are the days between the first scheduled appointment start date and the start date recommended by a healthcare professional (usually for a specialized clinic), Type II delays are the time between the patient arriving at the clinic until they are called by a medical assistant (Alvarado, 2018). Type III delays relate to later processes and so are out of scope for this thesis.

3.2.3 Multi Appointment Clinical Admission

Some patients, due to a mixture of logistical and medical reasons have to schedule multiple appointments for different resource types over a set period of time. Instead of walk in patients or single appointments these multi appointment patients have a specific path of visits to follow and a delay in one appointment can cause negative health effects (Marynissen, 2019). Despite this key difference between these patients and the other two types, the admission process does not appear to be different for multi-appointment patients in the literature reviewed.

3.3 Hospital Service and Quality of Care

A high quality of care for a healthcare clinic is crucial for a multitude of reasons. Most importantly, the dangers of poor quality of care can lead to patients not receiving proper care at the proper time which can have dire effects (Moshier, 2013). Even a low quality of care that does not cause these effects may still hurt customer satisfaction and can lead to a poor reputation, which can financially ruin a clinic. DES is often used for quality of care research into health clinics, especially around waiting times as they are considered the most crucial metric by most (Gunal, 2005).

An important factor in wait time is the arrival rate of patients and scheduling patient appointments. There has been a great deal of research into scheduling patients, which shows the more uneven nature of healthcare inter arrival times for patients as it both based on patient availability and their physician's availability (Hyytiä, 2019). Due to these factors, most healthcare facilities have an uneven interarrival time. As higher demand hours can cause wait times to drastically increase for a specific time compared to the average, simulation models also focus on hourly results of wait times and process times for a clearer picture of efficiency (Findlay, 2011).

3.4 Centralization and Consolidation of Clinics

While consolidation of clinics has been a growing trend for several years, only a few papers have researched the effects of centralization on the admission process and the environments in which it performs better than decentralized admission. Research into labor-management for consolidated clinics show a large improvement in controlling costs, optimizing resources, and an increased foothold into the local economies (Fox, 2013). Research into patient flow showed that even when patients had to move from the central clinic to another clinic in a centralized model, that having a high mobility of patients is not necessary in order to improve the wait time. Even with 10% of patients being able to travel one of the two hospitals saw a clear reduction in wait time while the other hospital had no change (Enrique, 2018).

While this model does show results in favor of centralization, it only focuses on two healthcare clinics, and is focused on the specific MRI process, and is for the longer wait time in terms of days of making appointments, whereas this thesis is focused on the criteria that best suits each system and is centered on delays once the patient arrives at the clinic.

4 Methodology

Due to the varied conditions in which a centralized and decentralized approach could be tested against each other, an initial general conceptual structure is presented to model the previously mentioned input as well as incorporate the remaining patient flow. Then a conceptual model based on a real-world healthcare organization will be presented to show the application of the general conceptual model and the extensions and adaptions made to fit the real-world scenario. Finally, the implementation of the conceptual model into a DES model is shown to illustrate the practical application of the conceptual model.

4.1 Centralized and Decentralized Healthcare Clinic Admission Systems

In this section, centralized and decentralized healthcare clinic admission systems are described including typical layouts and processes.

4.1.1 Decentralized Healthcare Clinic Admission Systems

Figure 1 shows an example of a general clinic comprised of the three different sections of the clinic, the waiting room, assessment room(s), and examination room(s). This is a very general layout for an average clinic, as whether or not there is an assessment room depends on the clinic and its needs. However, for many clinics, this is a somewhat reasonable expectation. The three rooms are usually supported by different resources, in this case, the receptionists, medical assistants, and physicians. Each part of the process is dependent on the availability of those resources and acts as a pull on patients upstream in the process.

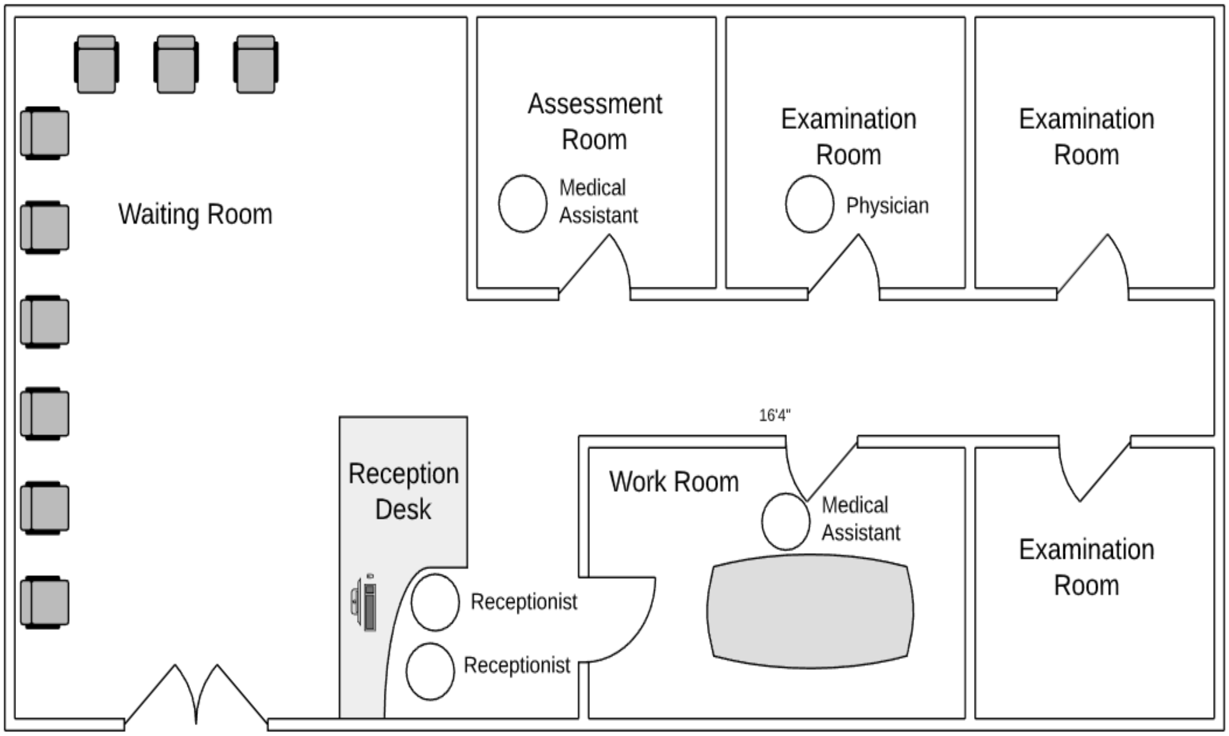

Figure 1: Example of a Decentralized Clinic's Layout

A receptionist provided patients with paperwork that the patient fills out while in the waiting area, though the time this task takes changes based on several factors, such as if the patient has insurance or not. The patient then waits to be called by one of the medical assistants, who takes physical measurements and asks questions about the patients' medical history and leaves the patient in the examination room to wait for the physician. As there were no appointment times that both the patients and the clinic had to uphold, the most crucial metric found was the service time of physicians and especially the average waiting time of patients. Figure 2 shows the general process of the walk-in clinic, and while there are significant differences between walk-in clinics and appointment-based clinics, the general process functions nearly identical.

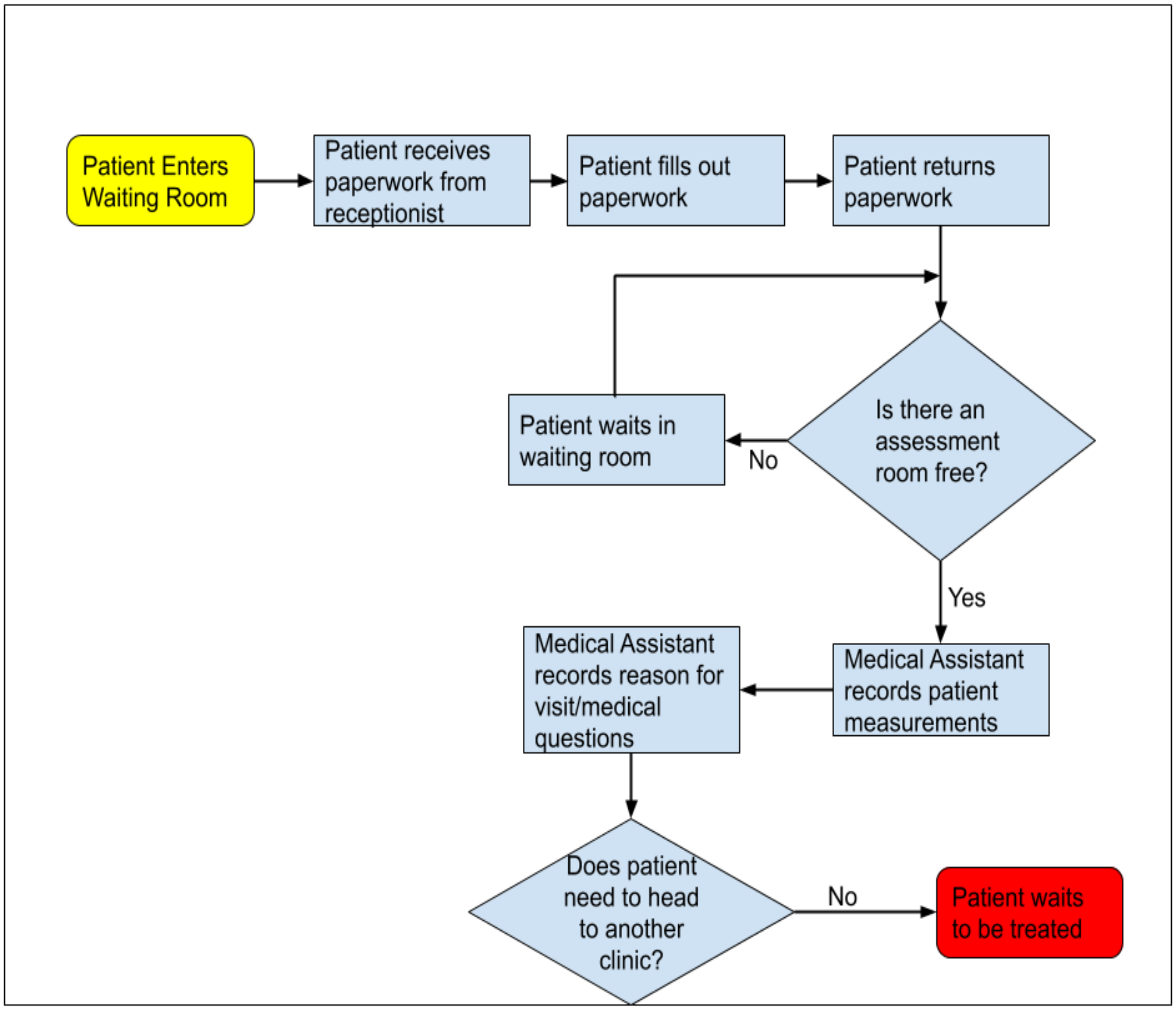

Figure 2: Process Flowchart for Decentralized Admission

4.1.2 Centralized Healthcare Clinic Admission Systems

Figure 3 shows the centralized version of a general admission process. While most steps are similar to those seen in Figure 2. The primary difference is once the examination process is done. If the location of the admission process is also the location of that patient's final clinical destination, then they wait until a physician becomes available. If not, then they head to their clinical destination and wait there for their physician. This second option will take more time than the first in terms of traveling, but depending on Physician utilization either option can have a longer waiting time.

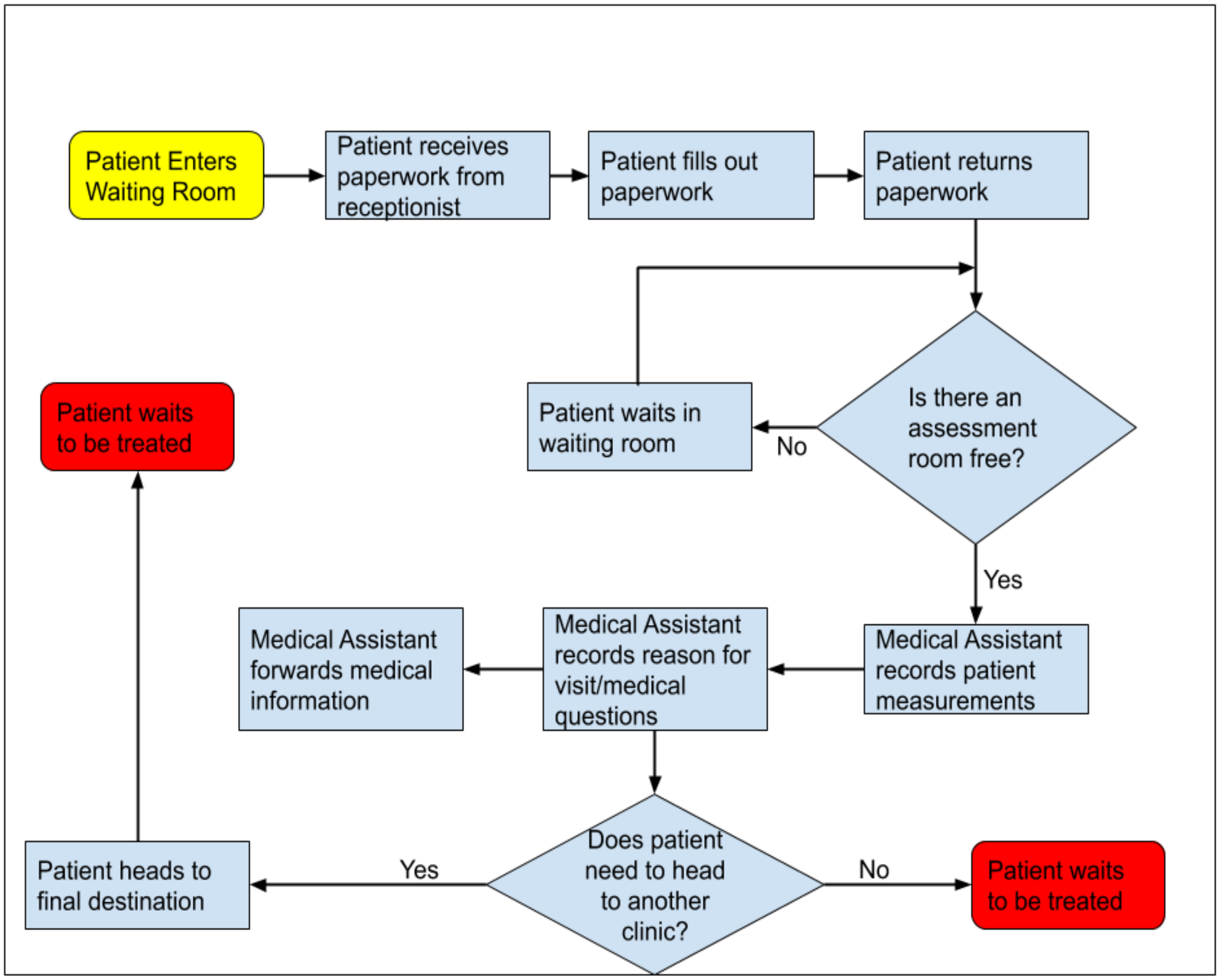

Figure 3: Process Flowchart for Centralized Admission

The Physical Layouts of Clinics would be altered by centralization as shown in Figures 4 and 5. Figure 4 shows a possible floor plan for the centralized admission location, which in this case is located within one of the clinics. In this centralized location, the number of seats in the waiting room has increased as well as space within the waiting room itself. Receptionists from the other clinics that are being consolidated have been sent to the central location bringing the number of receptionists to three, which can handle the admission process of at least three clinics depending on the registration process and the capacities of the receptionists.

Figure 5 shows another clinic in the cluster that does not have the central admission located in it. In this case, there is only one receptionist who would perform any necessary handoff procedures in place as well as any additional steps required for that clinic. As the number of receptionists and waiting room size capacity needed have decreased for that clinic, the floorplan was restructured to capitalize on the empty space by creating another examination. In a scenario where there were 3 decentralized clinics with similar floorplans to Figure 1, centralization may result in one facility similar to Figure 4 and the redesign of the three clinics from the floorplan in Figure 1 to the floorplan in Figure 5.

The one centralized location represented by Figure 4 would handle the registration and consultation sections of the admission process and therefore would consist of only a waiting room and assessment room. While the redesigned clinics in Figure 5 would still require a receptionist to greet the patients who have gone through the central admission and handle any handoff steps, the assessment room in those clinics can be changed into another examination room allowing for more patients to be seen. And as all assessment rooms are located in the central admission facility there should be no need for medical assistants in each clinic once centralized.

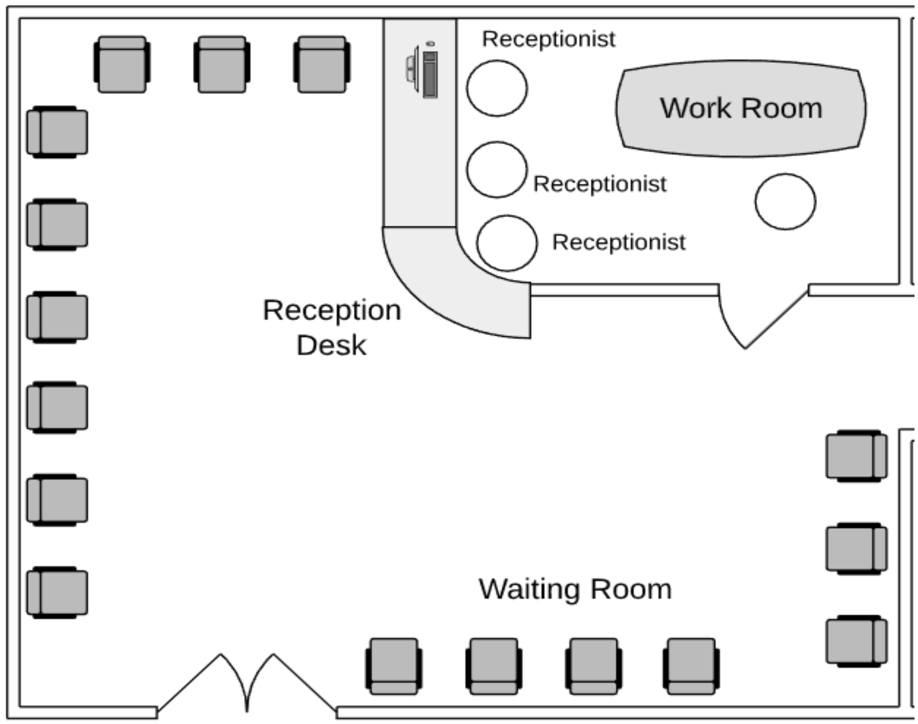

Figure 4: Example of a Centralized Clinic (Central Admission) Layout

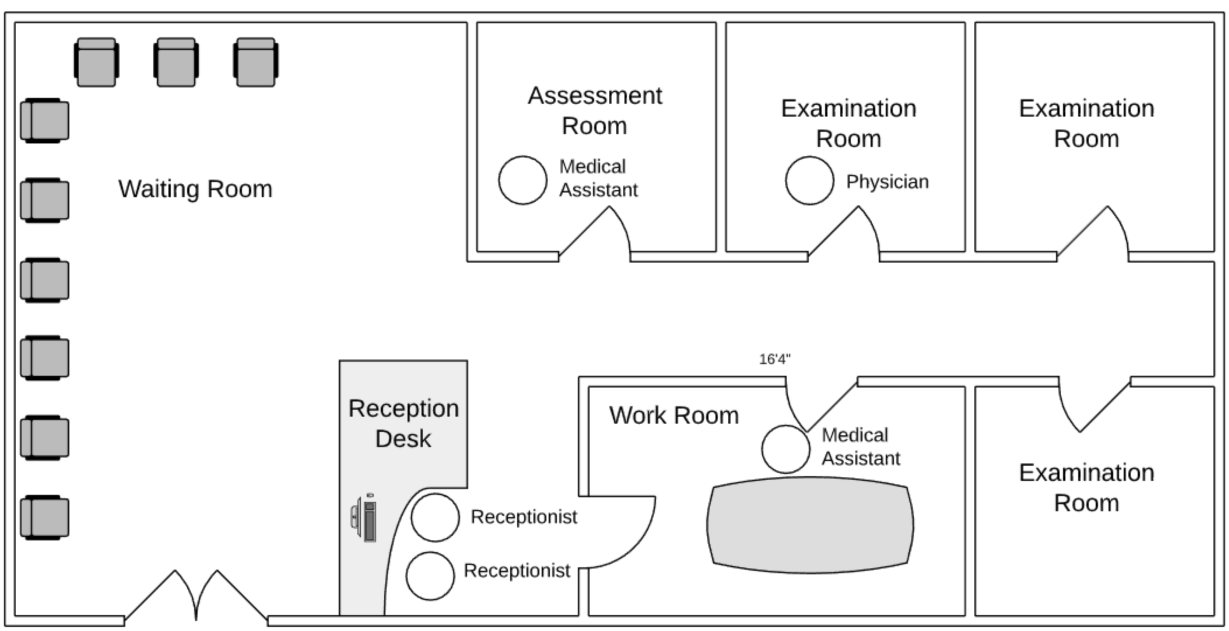

Figure 5: Example of a Centralized Clinic (Not Central Admission) Layout

4.2 Design of a Simulation Modeling Framework for Comparing Centralized vs. Decentralized Admission Systems

To evaluate decentralized versus centralized healthcare clinic admission processes, we design a simulation-based methodology. In particular, the methodology is designed to enable healthcare clinics to compare the operational costs and benefits of each alternative. Furthermore, the methodology is designed to study the factors that influence the performance of decentralized versus centralized clinic admission processes and under which conditions one alternative may be preferred over the other.

The overall design of the simulation modeling framework is shown in Figure 6. At the center of the framework is a modular DES model that simulates the operational aspects of the healthcare clinic admission process for multiple clinics. The model requires a detailed set of inputs for each of the clinics, the user can specify whether the simulation model will be run under the condition of a centralized or decentralized admission process. In addition, the user can specify a set of simulation experiments/scenarios to be conducted. Finally, a set of output performance measures are produced by the simulation model for comparing the operational performance of the system alternatives under consideration. In the next subsections, we describe each of these framework components in detail.

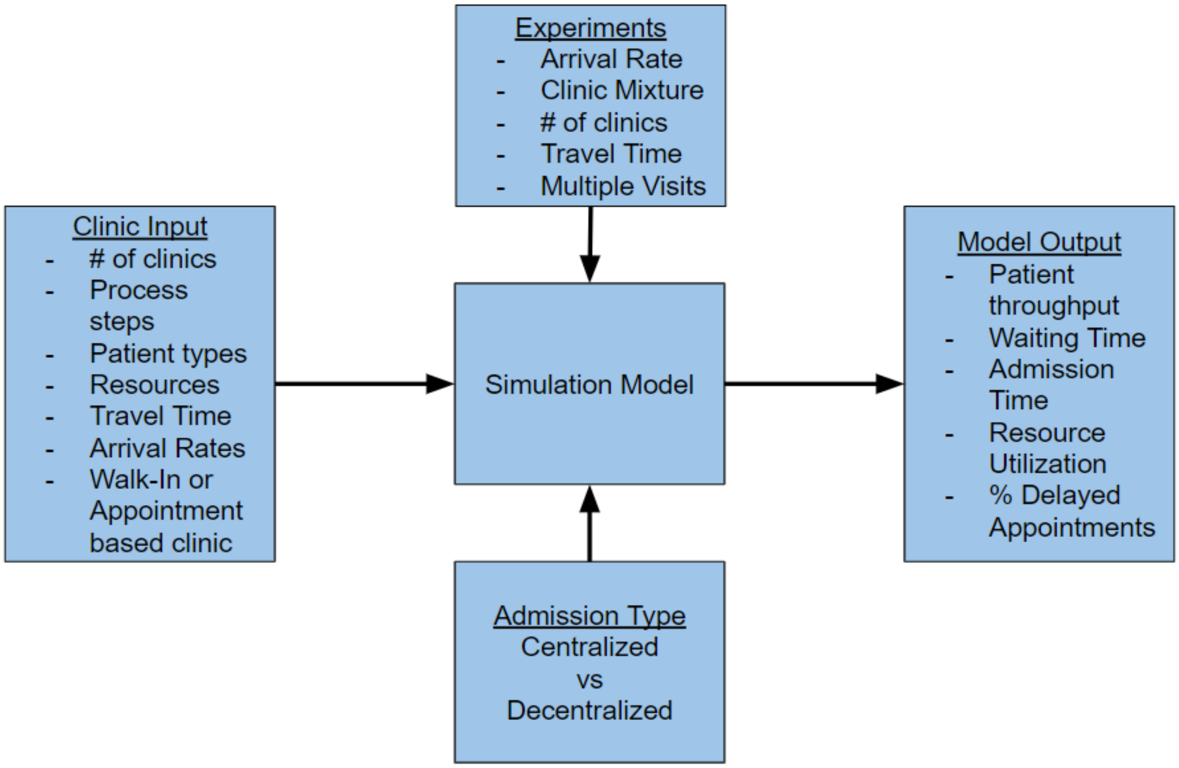

Figure 6: Simulation Modeling Methodology Framework

4.2.1 Simulation Model Inputs

To determine the conditions in which each admission approaches work best, significant data is needed from the clinics that are being considered to be consolidated. The information is generally split between time data and process data. As each clinic will most likely have different interarrival times, historic data, or reasonable estimates of patient arrival is needed for each clinic (Law, 2006). This data can be used to create flow patterns and for the sake of this model it can either take the form of hourly arrival data or distribution for the entire day, as long as it is consistent across the clinics being modeled. The arrival type for each hospital is an incoming patient that requires treatment directly tied to one clinic, as many clinics are specialized to cover certain fields of medicine. For operational reasons to run the model, patients know which clinic they need to go to and multiple clinical trips are included in the model. The likelihood of one patient going for treatment in one clinic after being admitted and then going directly to another clinic inside the consolidated center without being readmitted appears to be very low. However, certain consolidated clinics may have this experience in the real-world, and information from a real-world healthcare organization placed the likelihood for these patients at 10 percent. Excluded from the model are patients who go to the wrong clinic, leave before checking-in, and otherwise leave the patient flow. The model can be adapted to include these patients but for the thesis, these types of patients are considered outside of the scope.

At the most basic function, each clinic only has one type of patient arriving at the clinic with the same admission time distribution for each patient. However, in real life, there are distinctions between patients that can impact the admission process for a clinic. The most apparent of these distinctions is between new and returning patients (Sowle, 2014). Newer patients are more likely to have their admission take longer and depending on the clinic there may be additional steps for new patients that are not associated with returning patients. The model will include any distinctions given from the real-world large healthcare organization. There is also the concern of a patient not arriving directly to the central admission area and instead of going directly to their destination clinic. While some organizations may perform the admission at the destination clinics in that case of the misplaced arrivals, this model operates under the assumption that those patients would be redirected to the central admission and so are not included within the model.

The admission process for each clinic will be split into individual steps and gathered. Times for each step is needed, which similarly to the interarrival time could be a reasonable estimation or based on historic data. Steps requiring specific resources that are either unique or shared across the different clinics will be critical when designing the centralized hospital admission approach. Whether steps would need to be repeated if a centralized system is used would also be included and whether steps can be done concurrently or sequentially are key aspects of the model. The format of the steps will be based on research done on admission for a multi-specialty outpatient clinic (Mocarzel, 2013) which follows a process flow with several decision nodes.

A centralized admission system would cause handoffs of patients to be more commonplace and patient handoffs can increase the risk of complications and an increased length of stay (Fehlmann, 2019). While the most visible impact of handoffs in the simulation model will be repeated steps (if the clinic specifies any), the negative impacts of handoffs cannot be ignored. There has been research into handoff methods to reduce the negative effects of handoffs, with one finding the method done by a Cardiothoracic Intensive Care Unit (CTICU) to be the most effective (Collins, 2012). However, as it is an intensive care unit the amount and type of information are most likely different than many clinics being considered of being consolidated together. For the model, the handoff procedure of the organization in question will be used to determine process times for the centralized model. If any organization considering centralization does not have a handoff procedure in place they should research the best plan for their organization and determine its process time before making the decision to centralize. As the model ends once admission into the patient's clinical destination the later negative effects of patient handoff will not be incorporated into the model, but should not be forgotten when making the decision.

The admission layout for each clinic will be necessary, though the level of information will not have to include all dimensions of the clinical form, but key factors if a central admission will be located in that clinic; maximum capacity, number of reception desks, if there are any admission kiosks. Staffing will be an input into the model that can be changed between testing the two admission systems and will be direct information from the clinics in question. Distances between clinics will be required for the centralized models to determine time distributions between the central admission area and the patient's destination clinic. Reasonable time estimates would be preferred, but if only distances between clinics are known, the travel time will be given by a range of average walking speeds from .94 meters per second to 1.43 meters per second if the clinics do not require driving to get from one to another. If driving is required between clinics and no time estimation is given, data from Google Maps will be used to best estimate the times.

Admission processes change from clinic to clinic, so does the process the clinic views as falling under the category of admission. This thesis does not claim a standard definition, and so the extent of the effect of centralized admission can be modeled for further downstream in the process depending on the clinic being modeled. One of the largest decisions to be made is whether to include any post-visit operations into the model. These post-operation activities can be an important section of time and require the same receptionists who performed admission to perform the check-out steps as well (Al-Ashwal,2017). In cases were the check-out processes are performed by the same resources or impact the times of patients with multiple appointments, then the model should incorporate the process. However, this changes the endpoint of the model, and the method of modeling the clinic visit itself is tied into the decision on whether or not to have the check-out process modeled. As shown in Figure 7 below the decision of how much to include within the admission processes depends on how the secondary and tertiary steps are treated. Whether to separate the secondary step, the visit time, into smaller steps of assessment and examination depends on the operations performed by the healthcare organization.

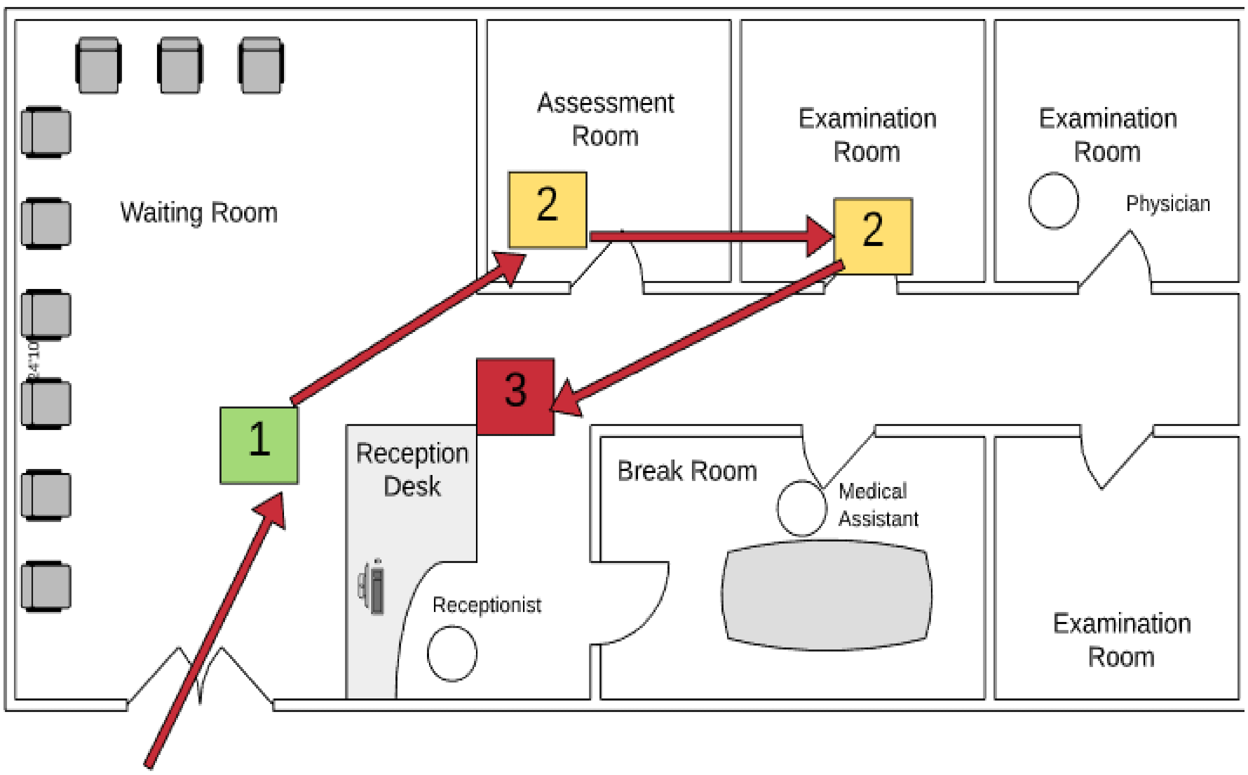

Figure 7: Separation between Check-In, Visitation, and Check-Out Processes

Including check-out processes can give a more accurate view of front desk worker utilization and patient wait times as shown in Figure 7 as both the check-in process and check-out process are performed at the reception desk. Often the check-in and check-out processes are performed by the same receptionist and in those cases ignoring the check-out process can give an incorrect view of the capacity of decentralized and centralized admission processes. Though as shown above, the visitation step has to be represented in some manner to understand the check-out procedure.

While the check-out process is an important consideration to model after the patient visit, the other primary concern is multiple appointments and the process associated with it. Depending on both the number of clinics, the correlation between clinics, and medical restrictions and limitations the number of patients who will visit more than one clinic in a single day changes from healthcare organization to healthcare organization. This is a significant population to examine however in terms of quality of care. As the patient will be going through at least two admission processes in a decentralized approach, they will most likely will be less tolerable of longer wait times. If the clinics are appointment based then there is a likelihood that a delay in an earlier appointment can cascade into future delays harming the entire schedules of some clinics and severe distress for the patient. Processes for multiple appointment patients can differ from those with only one appointment, and understanding the flow of these patients is key for the model to be accurate.

As previously mentioned, there is great variation in how clinics are run and interact with each other, as well as different definitions of what falls under admission from organization to organization. To account for this variation while creating a general model, some base components of any model was first identified, and then secondary components that could be added if they were relevant to the system being modeled. Figure 8 below shows the base concepts in the middle circle in the beige color while the secondary concepts are in the larger blue circle.

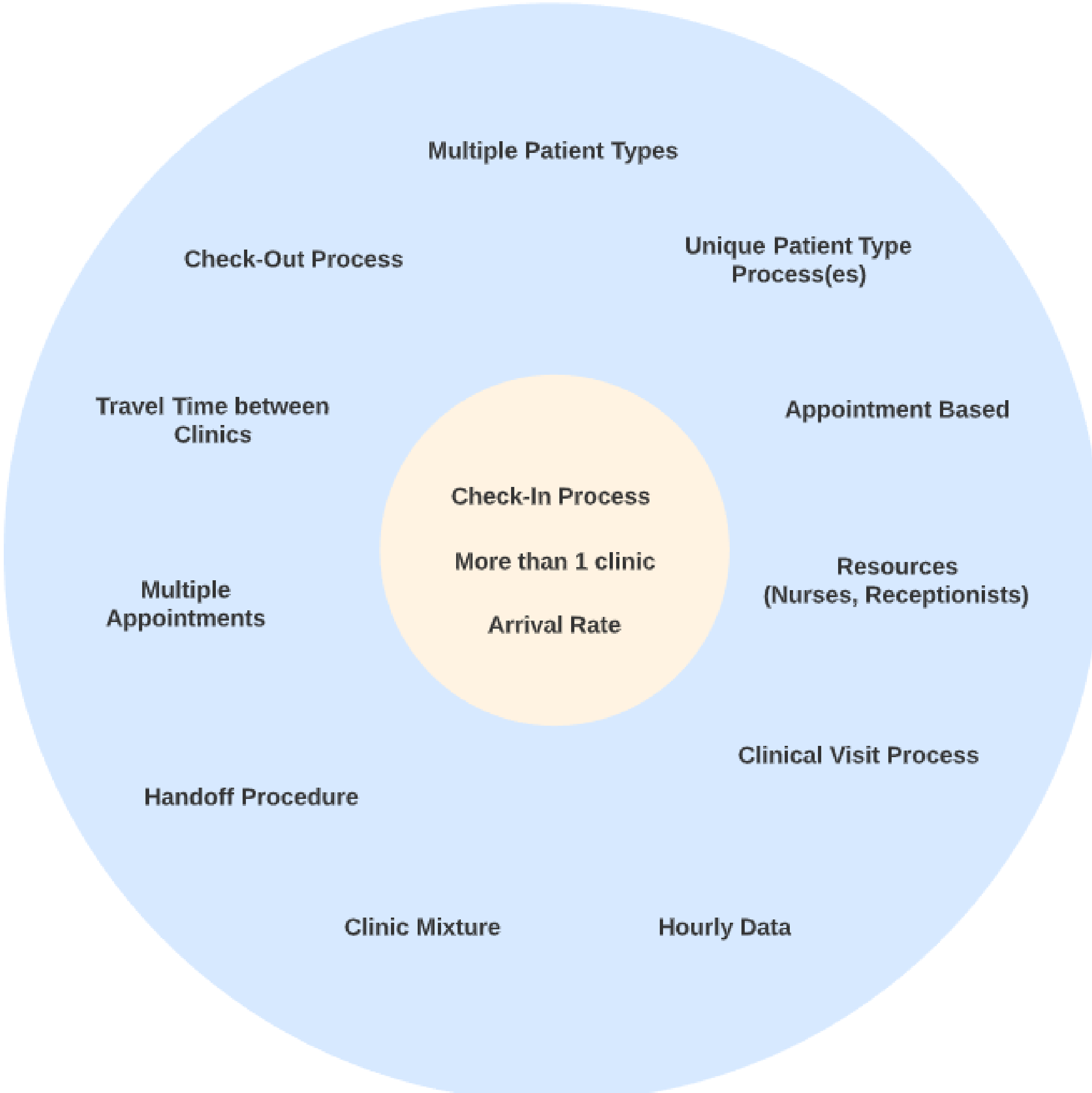

Figure 8: Base concept and Secondary concepts

The three main base concepts that appear in both centralized and decentralized models for any healthcare organization is that there is a check-in process, there is more than 1 clinic, and there is an arrival rate for a single patient type. The check-in process is the most conservative view of what should fall under admission, and if the organization wishes to stop there the patient visit to the doctor or healthcare professional will not be modeled. Instead, once a patient finishes going through the healthcare process they would leave the general view of the model. In reality, they would be continuing onwards with their treatment, test, or other reason to visit and then will most likely check-out afterward, but in the model, those steps would fall out of scope and the patient would have their times recorded before leaving the model. At the very least two clinics have to be compared against each other in a centralized model and a decentralized model. Finally, at least one type of patient has to be arriving at the clinics being modeled.

If the arrival rate is unknown then there is no way of accurately modeling wait times at the check-in process. These three concepts combined would be a good representation of a healthcare organization that does not have separate times for returning patients as opposed to new patients and has a few independent clinics with no flow of patients between them. In that case, the base concepts alone could address some concerns of that healthcare organization, but for other healthcare organizations, their needs would be unaddressed.

The secondary concepts cover a large range of additions that can be made to the base model, and since none are contradictory, and up to all eleven concepts can be added in if they are relevant to the real-world situation and the data needed is available. Going clockwise through the concepts the first is having multiple patient types. As previously mentioned, returning and old patients will most likely have different times for the same process. While a returning patient may only need to confirm that the previously entered personal data is correct, a returning patient may have to fill out the entirety of the personal data. In that example, returning patients who have recently moved or otherwise caused changes to their personal data could fall into a new patient type or their percentage can be included as a decision for one of the other two patient types. Other differences in patient type can be related to age or mobility if this also affects process and travel time in a significant way for the healthcare organization.

Related to this is the next concept of unique patient type processes. New patients may have to go to a registration center that returning patients will skip during their visit. The difference does not always have to be between old and new patients, another unique process could be phlebotomy which some patients may have to go to before heading to their clinic appointment. The process could cause further delays if there is a significant delay, and determining where to place the centralized check-in location should consider unique processes that may have an impact on patient flow.

Clinics can be either appointment based or walk-ins, though the base model assumes the latter option. However, if an organization has one or more appointment-based clinics they may wish to not only see the wait time for their check-in processes, but also the percentage of patients who are checked-in on time. As shown in the literature review, keeping appointments is a key factor in customer service. While walk-in patients may be more accepting of longer wait times, patients with appointments have a set time they expect the process to start and if it is not met this can reflect badly on the healthcare organization. Crucial to both the processes being modeled as well as the organizational needs of the clinics are the number of resources available to each one.

While some resources may be machines, the majority of healthcare organizations will most likely need to incorporate their nurses and receptionists as important resources in the admission process. If the clinics are understaffed, wait times for check-in will grow larger, though if they are overstaffed, the healthcare organization has increased costs for operation. Staffing is a key element of centralization due to some evidence of reducing operational costs including staffing (Fox, 2013). A centralized location for check-in will require receptionists to run, but will most likely reduce the capacity need at each clinic. Capacity can be modeled in different ways, either as the static capacity available for the entire run or an hourly worker schedule in which the capacity depends on how many receptionists are working each hour.

The clinical visit process itself is an addition that can be included in the decentralized and centralized model. Due to the high amount of variation, these processes can take it may be best to leave out, unless multiple appointment patients or check-out processes require that this step be modeled. The next secondary concept of hourly data is a crucial one for many healthcare organizations. Often, arrivals vary by the hour of the day, as the first hour the clinics are open will not have the same demand as during 11 am or 12 pm when many people may set up appointments. Certain clinics may experience hourly demand spike during different periods than other clinics. If the data is available or can be recorded, this can help give a more accurate view of the mixture of wait times at the different clinics over time.

Clinic Mixture refers to the percentage of patients going to each clinic. Without this addition, an equal distribution between clinics or an estimated distribution would have to be used.

Knowing both the arrival rate and accurate mixture of how many patients go to each clinic, combined with hourly data, can give the fullest view of the demand facing the check-in process.

The handoff procedure is primarily relevant in the centralized model as it is the process steps and times associated with a patient who has already been checked-in. For example, if a patient has gone through the admission process at the central check-in location, their information and answers need to be sent to the clinic the patient is heading to. There may be additional steps associated with this such as verifying the information at the destination clinic, and the full scope of the handoff procedure must be known before the creation of the centralized model to make sure the scope is accurate. Handoff procedures are very important for understanding multiple appointment patients which is the next secondary concept that can be included. Multiple appointments are more likely when a healthcare organization has many closely located clinics that have overlapping patients. In most decentralized systems these multiple appointment patients would have to go through the check-in process multiple times for each clinic. Due to this, multiple appointment patients can have a large impact on customer service and delay times for several clinics. A centralized check-in location can solve this by having only one check-in process for each patient, with multiple handoff processes for each clinic that the patient is visiting.

Multiple Appointment patients may fall under a separate patient type if there are any changes to process times, process paths, or additional steps that multiple appointment patients have to perform compared to single appointment patients. To determine which patients have multiple appointments is one of the more difficult aspects of the model. They could either fall under a separate patient type as mentioned before that goes through several clinics, or the decision to visit another clinic can be incorporated into the model after a certain process step.

Travel time between clinics is another crucial aspect to model if the clinics have interactions with one another. Especially in the case of multiple appointment patients, having both long travel times and long wait times are more likely to result in a negative experience, and healthcare organizations may have an easier time changing the latter delay. Depending on the distance the travel times can be estimated using google maps for travel times between non-adjacent buildings that may require some driving or a long period of walking. If the clinics are located inside the same building or on a single site, the travel time has to include how long it takes from one floor to another considering the methods of travel (such as elevators and stairs) the ease of movement (if two buildings are conjoined at every floor or while the patient has to travel down one floor to travel from building to building before ascending another floor) and the mobility of the patients (older patients or patients with mobility issues will most likely be more reliant on elevators and therefore dependent on their availability). These factors result in travel time becoming a large distribution of possible times instead of a static number.

Finally, if there is a check-out process, such as scheduling another appointment, that can possibly be added into the models as well. While most healthcare organizations would consider the check-out process to fall out of scope for admission, the process is most likely done by the same worker or resource that handles the check-in process. If the check-out process is ignored in this case it would appear that the only demand on the resource is incoming patients coming to the clinic. Whether the resource prioritizes patients checking in or checking out, or if patients are serviced in a first come first serve approach depends on the healthcare organization being modeled.

The check-out process can also affect the wait time of multiple appointment patients, especially if they have appointment times for their next clinic. As mentioned previously, meeting these appointment times is a key aspect in retaining good customer service, and as the check-out process can affect that in certain scenarios as well as staffing of receptionists, the process should be modeled if relevant.

4.2.2 Simulation Model Admission Type

Figure 9 shows a selection of secondary concepts used that will be shown in the general centralized and decentralized models. The choices made when selecting the secondary concepts has large implications for the structure of both the decentralized and centralized models as some inputs may relate more to one system than the other.

Figure 9: Base concept and Secondary concepts

The secondary concepts chosen can impact the inputs and outputs that are being shown by the models. Figure 10 shows the primary inputs and output of the clinics, along with the information needed from each clinic to create the model. From Figure 9 it is clear that the base concepts are all met, there are multiple clinics each with their own check-in process and arrival time. Some secondary concepts can be seen in the metrics, inputs, and outputs. Depending on the type of resources used, resource utilization will also be used as a key performance metric, along with throughput. Waiting Time and Admission Time are key metrics and the difference between the two patient types in regards to these times should be explored in the results of the model. There is an established handoff procedure between clinic as well as travel time which due to their not being multiple appointment patients will not be explored in the decentralized model but will be a key feature in the centralized model. The relationships between clinics are an important aspect in understanding the scope of the model.

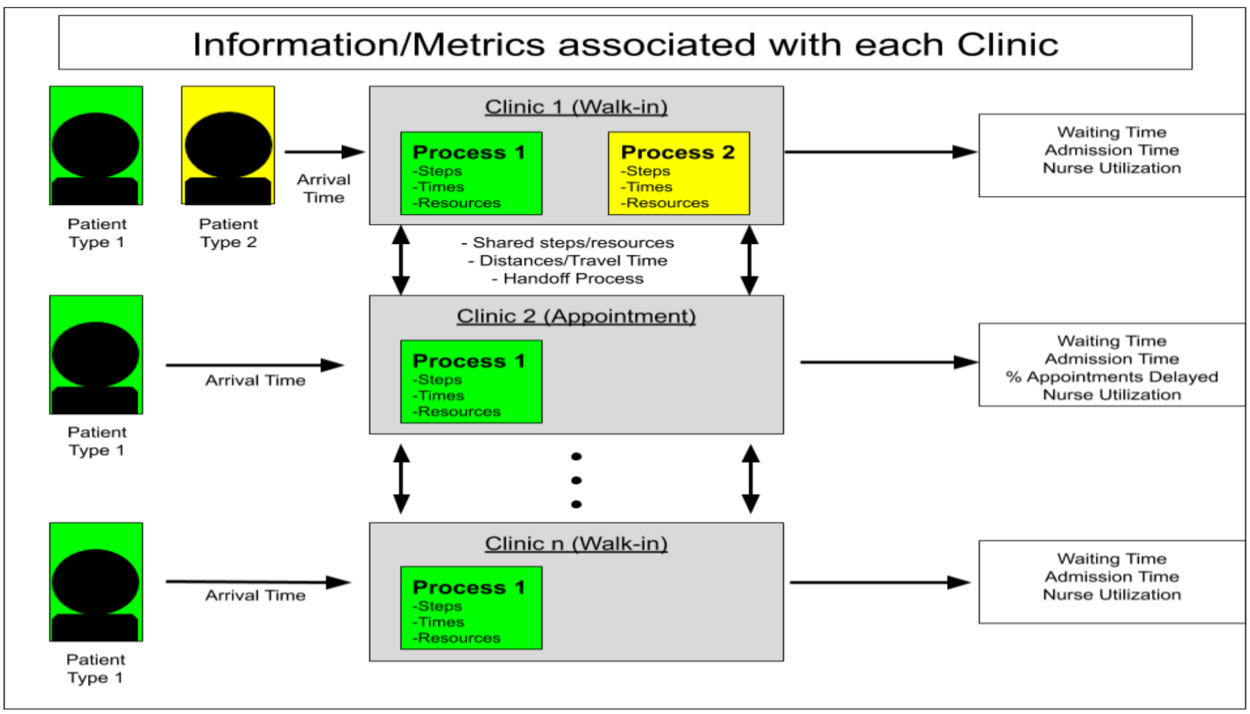

Figure 10: Information and Metrics for Clinic

Following the data collected in Figure 10 for all the clinics in the system and capturing the relevant secondary concepts in Figure 9, the decentralized model is generally configured in a similar manner to Figure 11 below. This example shows 3 clinics, one of which is appointment based and so has differing outputs than the other two. Clinic 1 has two patient types with differing processes, most likely a distinction between first time and returning patients. Therefore, the waiting time and admission time results for clinic 1 can be separated by patient type as well as a general clinical performance overview.

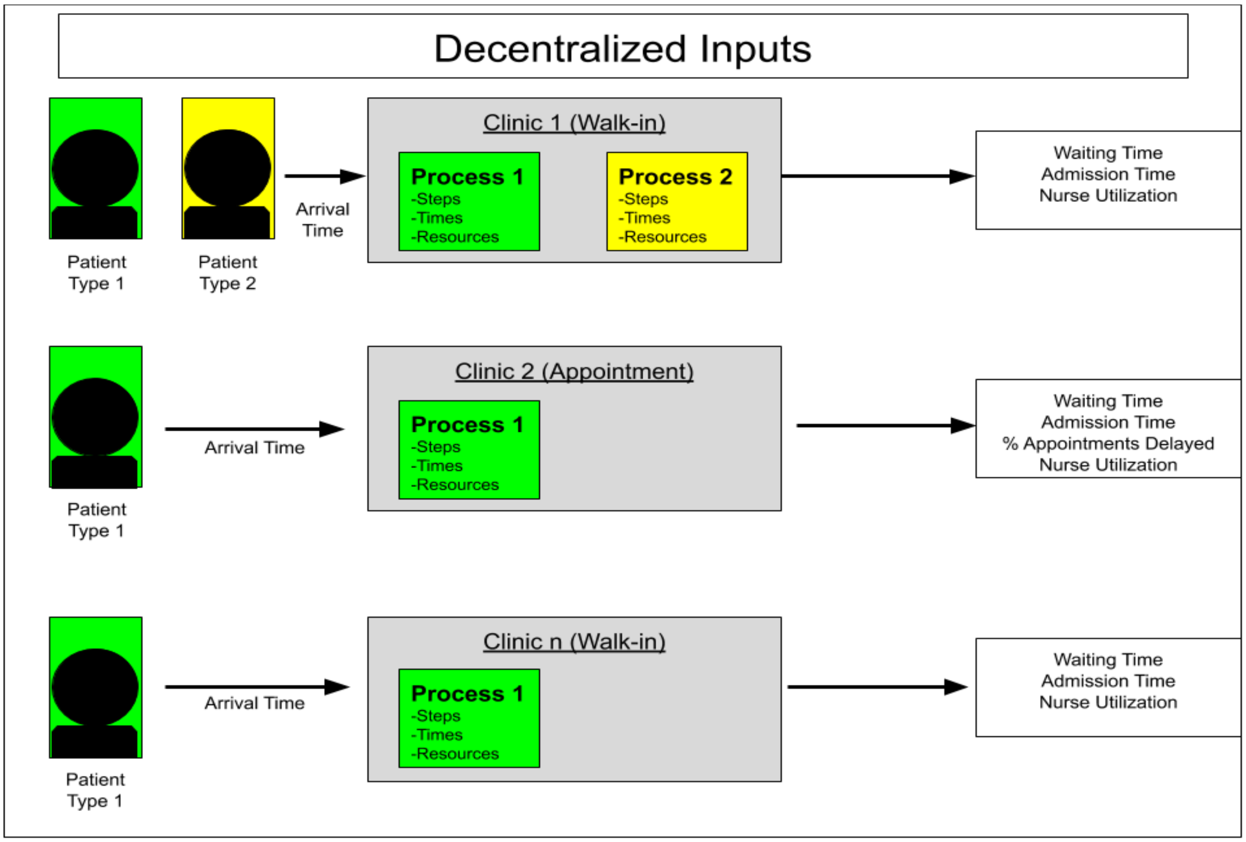

Figure 11: Decentralized Model Inputs, Setup, and Outputs

This example shows one of the more straightforward healthcare organizations as there is no interaction between clinics in the decentralized model as there are no patients with multiple appointments. There is also no clinical mixture of patients so the arrival time for each clinic is equal to the other two clinics. The only distinction in arrival is that clinic 1 has a secondary patient type that has a separate process. A decentralized model as this would be simpler to create in a DES model as the flow of patients is relatively straightforward, and with an equal distribution of incoming patients assumed for each clinic, the only data needed to be collected before creating the model is the number of resources, the processes (separate processes and resource-dependent steps) and the arrival rate.

A decentralized model similar to the one in Figure 10 would be able to show the ability of the resources of performing the processes in a timely matter. The primary concept of difficulty in modeling would be keeping an appointment-based metric for the second clinic separate from the other clinics. This may require designing the handoff procedure for the centralized clinics with the different admission systems in mind. As most current state scenarios for healthcare organizations are likely to have a decentralized admission approach, the decentralized model serves as both a benchmark and comparison with the hypothetical centralized location. In this regard, the goal of the decentralized model is not to be optimized in itself but to greater understand the effect of capacity and time that the change in admission strategy would have.

As the centralized model is most likely not the current state of the healthcare organization, two major decisions need to be made before modeling. The first is the handoff procedure, which bridges the gap between the new central admission process and the individual clinics. As shown in the literature review, there has been a great deal of research into handoff procedures, though they will of course vary by the healthcare organization, depending on the information that they need to capture and send to the next clinic.

The second important decision is where to place the central admission location. As shown in Figure 11 the central admission location is in clinic 2 where the remaining patients in clinics 1 and 3 get rerouted from. Many factors can impact the location of the central admission, the most important of which are distances from the other clinics, resources available at that location, and the size of that location. In this example it is assumed that clinic 2 can rearrange their space to handle the increased size of a central admission desk without hurting their operation. The central admission location does not necessarily have to be set inside another clinic. If there is another location that meets the three main factors above, then using it would give more flexibility than restructuring an existing clinic's layout and possible interrupting services for that clinic. Travel times between clinics are an important consideration and the mobility of the patients has to be considered when choosing a central location and estimating the travel time.

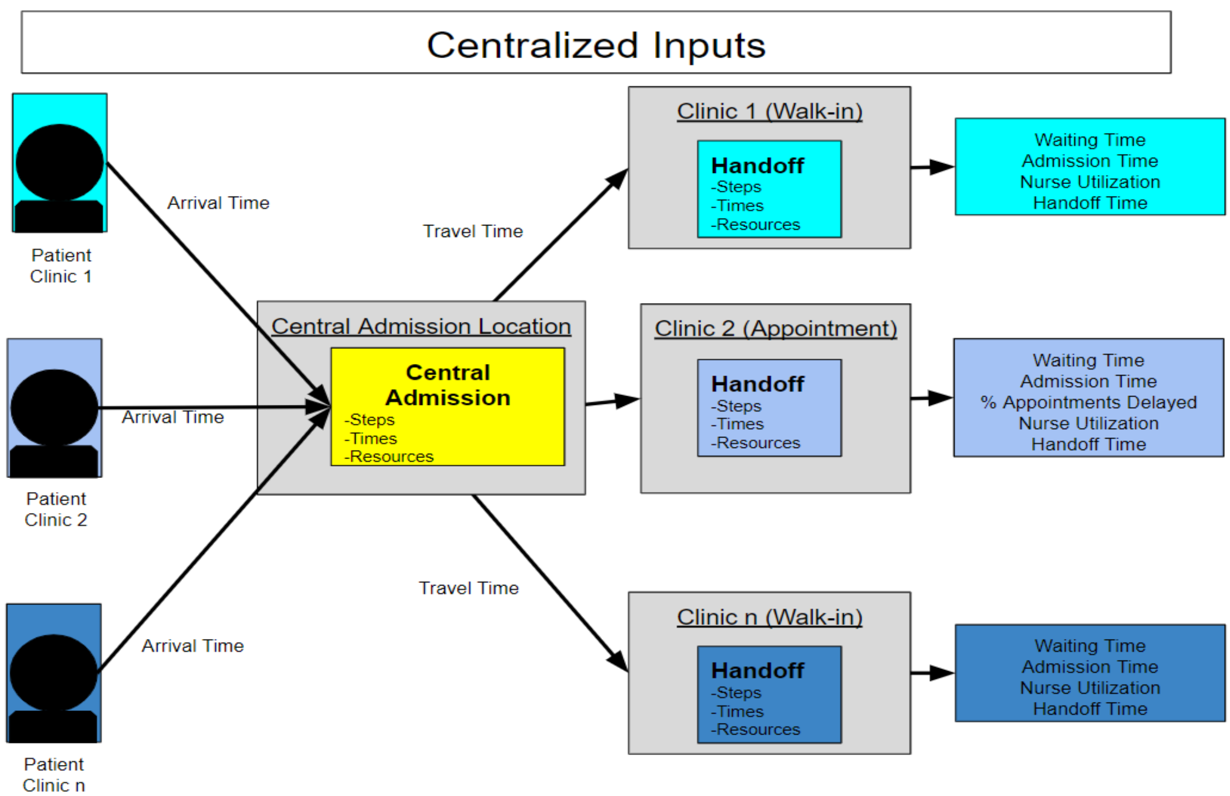

Figure 12: Centralized Model Inputs, Setup, and Outputs

For both the centralized and decentralized general conceptual models, adding a new clinic would be an easy procedure, allowing for the model to increase or decrease in scope.

4.2.3 Simulation Model

Creating useful decentralized and centralized models required going to a large healthcare organization and receiving real-world information from them. Besides obtaining the information needed to build a model that reflects a real scenario instead of one based on estimations, the consultation with the large healthcare organization led to a greater understanding of crucial metrics and areas of increased importance. A physical overview of the clinical steps is seen in Figure 13.

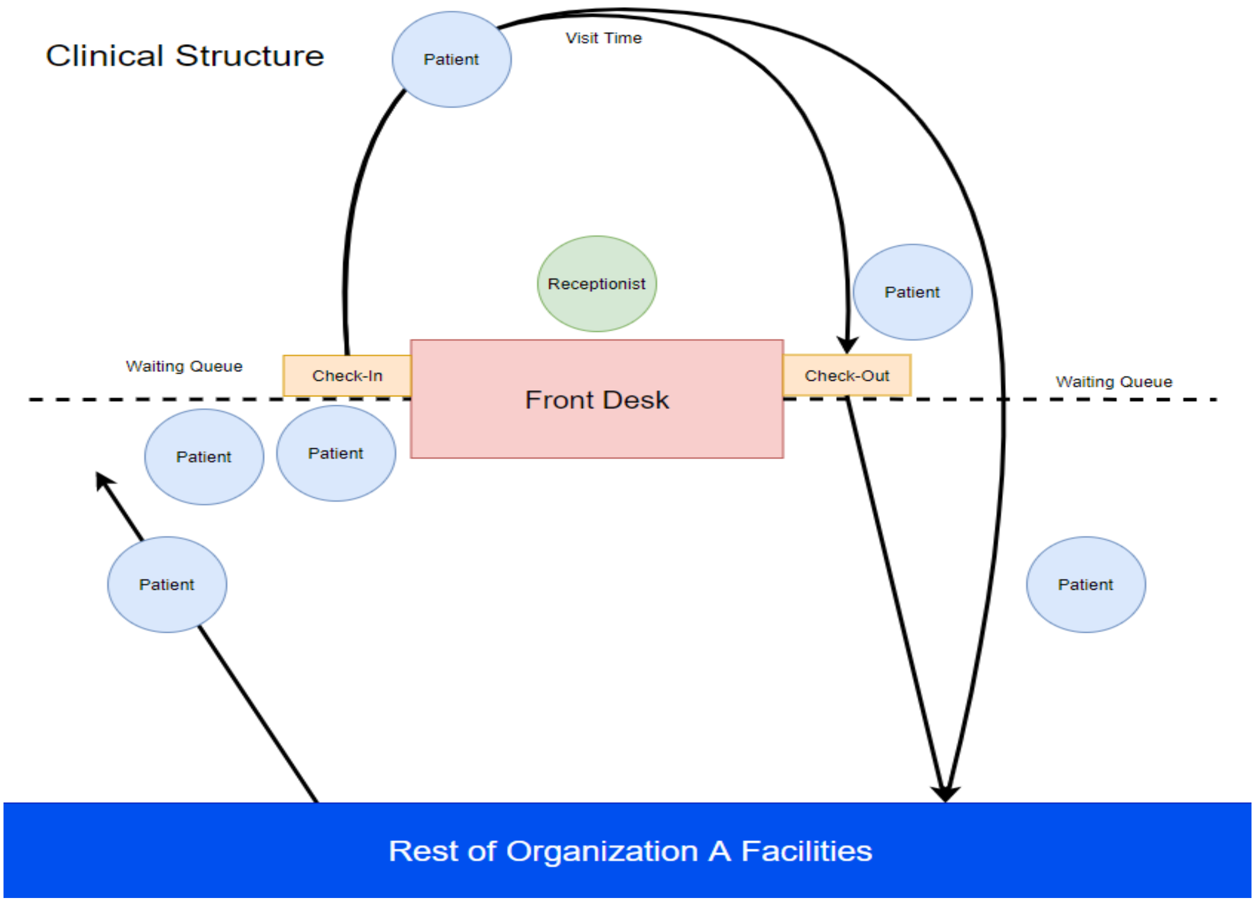

Figure 13: Physical Patient Flow at a Clinic

Both the check-in process and the check-out process are performed by the receptionist(s) working at the front desk of that clinic. The receptionist is equally split between those processes, no receptionists are solely for check-in or check-out, and will perform whichever task has a patient waiting for them. The number of receptionists changes from clinic to clinic and for the model the receptionists are available for all 12 hours. So, while a clinic may have 1 receptionist in the model, in reality, that role may be filled by two 6-hour work shifts.

The receptionist capacity for each clinic are not given work hour schedules to give the healthcare organization considering the change the ability to choose the staffing based on capacity. As there are many regulatory and operational factors to staffing that are out of scope for this model, the number of receptionists refers to the number of receptionist roles at that clinic and not the exact staffing. In regards to the model, each receptionist can only help one patient at a time. Therefore, if there are two patients approaching the front desk for check-in and there is only one receptionist then the second patient must wait for the initial patient to go through check-in. In that example, the receptionist is also responsible for the check-out process as well. Receptionists serve the patients on a first come first served basis, and so a patient ending their visit and heading to the check-out would be served first before a patient arriving a few seconds later. This logic can change depending on the organization if either check-in or check-out is prioritized, though from talks with a large healthcare organization with several clinics this is the strategy that is used there. While receptionists do perform the check-in and check-out processes there are also other more infrequent actions that are not inside the scope of the model. One example is for patients who have missed their appointment times, receptionists will usually call the patient a few times given there are no patients currently checking-in or checking-out. There are also more administrative smaller tasks as well as breaks that are not included, therefore the times in the model are not all-inclusive or all the receptionists' actions, making the capacity results more likely on the lower end than reality. Therefore, the result that one receptionist can handle the entire day's capacity for one clinic is possible in the model but not necessarily in reality.

Table 1: Number of Receptionists at each clinic in the Decentralized Model

Clinic Number	Number of Receptionists	Clinic Number	Number of Receptionists
Clinic 1	2	Clinic 9	3
Clinic 2	4	Clinic 10	2
Clinic 3	2	Clinic 11	3
Clinic 4	4	Clinic 12	2
Clinic 5	4	Clinic 13	1
Clinic 6	3	Clinic 14	1
Clinic 7	4	Clinic 15	1
Clinic 8	4	Clinic 16	1

Table 1 shows the current state receptionist capacity for each clinic. For example, for all 12 hours of the model, there are 4 receptionists at Clinic 8. Overall there are 41 receptionists across the 16 clinics. As the Decentralized Model is the current state the number of receptionists matches the real-world capacity. As receptionists are the key resources for the clinics, the number of receptionist roles at each clinic has a large impact on the waiting time of patients both at check-in and check-out. The utilization of these receptionist resources is difficult to gauge with the missing breaks and additional processes, but viewing the wait times for both the check-in and check-out processes can inform the decision to add or remove a receptionist resource.

Table 2: Percent Rerouted to Next Clinical Appointment

Clinic Number	Percent Likelihood	Clinic Number	Percent Likelihood
Clinic 1	3.47%	Clinic 9	8.47%
Clinic 2	7.06%	Clinic 10	5.01%
Clinic 3	4.24%	Clinic 11	14.89%
Clinic 4	8.34%	Clinic 12	4.62%
Clinic 5	8.09%	Clinic 13	2.18%
Clinic 6	7.83%	Clinic 14	3.08%
Clinic 7	10.91%	Clinic 15	2.70%
Clinic 8	6.55%	Clinic 16	2.57%

Table 2 shows the likelihood each patient has for their next appointment. When leaving their first clinic, whether or not the patient went through the check-out process, the patient has a ten percent chance of having an additional appointment. If that is not the case, they will leave the model and have their information recorded. If the patient is part of the ten percent who does have another appointment then they are assigned a new clinic. Not all clinics have an equal chance of being selected, and Table 2 shows that some clinics are more likely to be rerouted to. A patient who has an appointment after visiting clinic 3 is more than four times more likely to visit Clinic 11 than they are to visit clinic 1 for their next appointment. However, patients cannot go directly to the same clinic. If a patient leaves Clinic 16, they must go to a new one if they have an additional appointment. This cycle can repeat multiple times, starting at Clinic 1 then Clinic 6, and then Clinic 14. If so, their travel time and waiting time at each clinic are recorded together.

The structure of the centralized model is very similar to the decentralized model. The major differences between the two are the two key decisions for the centralized model, the location of the central admission clinic, and the handoff procedure. These are major decisions when planning a centralized admission system, and certain organizations may choose to locate the central admission location inside an existing clinic or in a totally new facility.

Space can be made available and that location is the easiest to get to as a majority of patients enter through the main lobby. This would also reduce travel time as compared to a central admission location located on a higher floor of either building. In that scenario, the patient would have to ascend several floors even if they only have a single appointment for one of the clinics on the first floor. However, since the central admission location is now another stopping point on the path of the patient, the travel time to the central admission location and the waiting time in the queue for the central admission are also compounded with the rest of the patient's travel time and waiting time. If the clinic's check-in wait time remained unchanged from the decentralized model then this additional central admission location step would lead to a longer total travel and wait time in every scenario. However, the handoff procedure reduced the time it took for the check-in process, where the average combined total for the central admission location check-in and the handoff procedure at each clinic.

The remainder of the visit time and check-out remain unchanged from the current state and rerouting still follows the distribution of clinics seen in Table 2. One advantage of the centralized check-in is if a patient visits two clinics, instead of performing the same decentralized check-in process for both, the patient will only have to do the longer central admission and the shorter check-in twice. As the central admission and a singular clinical destination in the centralized model takes roughly the same amount as one clinical check-in in a decentralized clinical visit. A patient with three clinical visits will, therefore, have a much smaller overall process time in the centralized model as the central admission process is never repeated.

While the setting of the central admission location and the handoff procedure and new check-in times were all known, the central admission's main point of ambiguity are the receptionist resources. This will be covered in the experiments section, and if the central admission location and handoff procedure were also unknown these could have been changed from experiment to experiment to determine the most optimal placement and cutoff point, respectively.

To model the decentralized and centralized models, the simulation software Simio was chosen. This was due to its ability to model the concepts and data needed as well as its availability and the experience with the software. Two separate but similar models were created to learn about the effects of centralization compared to the decentralized model based on real-world data. These models were made to be modular in the sense of making adding in new clinics and changing process times and mixes as easy as possible. In fact, the scope of the models did change several times and additional clinics were added to the models in relative ease.

While it would have been possible to use other software for the modeling, the visual aspects of Simio made observing patient flows and wait times easier to see, and Simio's add on processes were able to cover the range of decisions in the process. The two models were not created simultaneously as the centralized model was heavily based on the decentralized current state model and therefore was heavily based upon the latter model.

The first aspect of the decentralized model that was created was the source of the model entity, in this case, the patient. The patient arrives into the model at a speed dependent on the rate table. A standard table was used for the percentage of the total day's admission for how many patients arrive each hour, where the number would vary based on the total day's admission. Therefore, five different rate tables were created using the hourly distributions in Figure 15. As the average amount of patients is 779 patients per day, the other arrival rate tables were 25% and 50% higher and lower than the average as shown in Table 3. Patients arrive through the source at the rate of one patient at a time. While the arrival rate includes not whole numbers, the variation in the arrival rate tables made the actual number of patients who went through the model always a whole number and often varied from the arrival patient by a few patients. This variation is more accurate to the real-world scenario and also was the reason for the larger intervals between the arrival rate tables, as a ten percent increase would have most likely coincided with the average arrival rate.

Table 3: Arrival Rate Tables

Rate Table	50% Lower	25% Lower	Average	25% Higher	50% Higher
Patient #	547.73	730.31	779	973.75	1095.47
Hour					
1	5.59	7.45	7.95	9.93	11.18
2	33.47	44.63	47.61	59.51	66.95
3	79.18	105.58	112.62	140.77	158.37
4	92.71	123.62	131.86	164.82	185.42
5	86.81	115.75	123.47	154.33	173.63
6	61.87	82.49	87.99	109.99	123.74
7	59.63	79.50	84.80	106.00	119.25
8	63.50	84.66	90.31	112.88	126.99
9	43.38	57.84	61.69	77.12	86.76
10	18.73	24.98	26.64	33.30	37.47
11	2.62	3.50	3.73	4.66	5.24
12	0.28	0.37	0.40	0.49	0.56

When a patient arrives according to one of the five arrival rate tables, they then are assigned an arrival hour. The arrival hour is the ceiling of the patient's arrival, for example, a patient who enters at 6:05 AM would be assigned an arrival hour of 1 as that is the first hour being modeled. This does not affect the times of the patient, but rather where the patient's metrics are being recorded. When a patient arrives through the patient entrances source, information about where certain time and decision probabilities are read from are assigned to them to make sure the model chooses the accurate times and likelihoods.

The best example of this is how the model reads two tables to determine which clinic the patient is assigned to. To account for this, the decentralized model has two tables, one of which has the likelihood for all clinics being chosen for all 12 hours, and another table that selects sections of the larger table by hour. For clinics that are not open for the first hour or last hour, they would have a zero percent chance for those hours. Generally, clinics will have one or two spikes during the middle 6 hours of the day but will otherwise remain somewhat level. However, while percentages of the mixture may remain level for a clinic, the number of patients who arrive each hour varies so the number of patients per clinic changes per hour even if the mixture does not.

As shown earlier there were no different patient types, though new patients and patients who had phlebotomy appointments were briefly considered to be separate entities. In the final decentralized model, there is only one model entity, the patient. That means that all patients are treated the same way, they have the same chances of choosing clinics and process steps and choose their times from the same distributions. To understand the entire model, it is best to start with a generalized view of the entire model as shown in Figure 14.

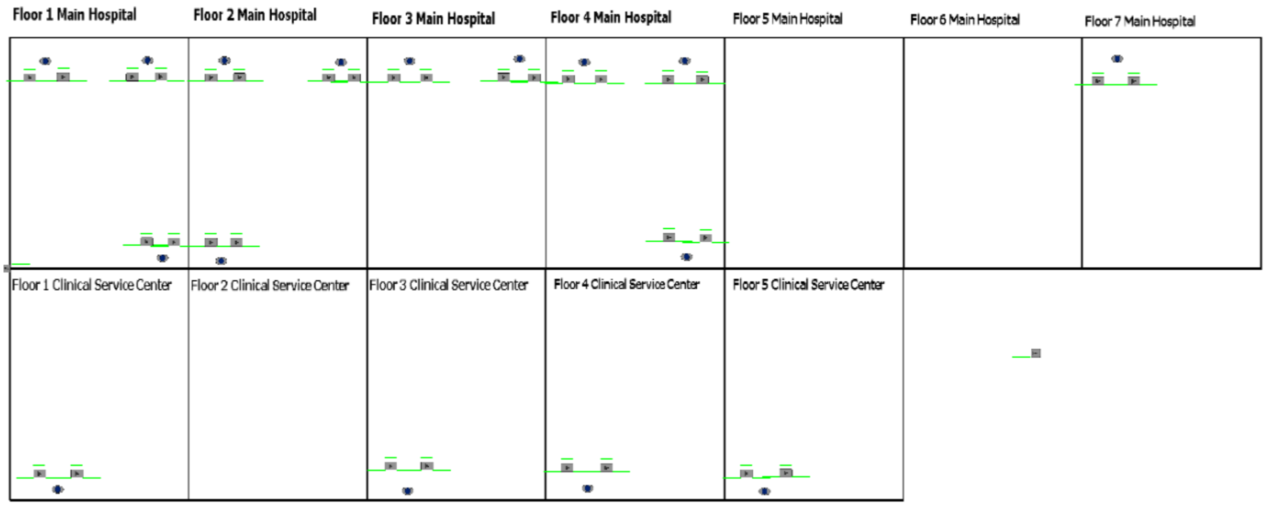

Figure 14: Decentralized Model Overview

Figure 14 is an abstract version of two facilities, where each floor is represented as a square box. There are certain floors with no clinics that fell within scope but are included in the model to give context for clinics on higher floors. There are several floors with only one clinic in the model, though three floors have three clinics each. Each floor has a node located near the center of the floor. The first example is when a patient leaves the entrance. As patients enter through the lobby of the main hospital they are sent to the node in the first floor of the main hospital. That node has 16 different pathways that lead to each clinic. Each pathway has the time associated from that node to that clinic as well as a piece of logic to make sure only the patients assigned to that clinic travel on the path from the floor's node to that clinic. An example of this is seen in Table 4.

Table 4: Hourly Mixture of Clinics

Travel Time	TravelTime.SH0F
Selection Weight	ModelEntity.ClinicNumber ==1

Table 4 is the same logic for all time paths in the model. As each floor that has at least one clinic has a node, and each node is connected to all 16 clinics, there are in total 144 time paths that follow Table 4. The first row reads a specific column in a table that contains all travel time distributions as described in Figure 13. If the time path is a connection from the first floor of the main hospital to clinic 1 then they would have the same exact setup as Table 4. Each column of the travel time table has whether or not the location is in the same hospital/facility and the same floor. In the case of the travel time table, SH0F refers to the same hospital and 0 floors distance which is the same floor, which means the travel time is a uniform distribution of (.25,.75) minutes. The second row is used as logic to make sure that only the patients that are assigned clinic 1 take the pathway from the first floor in the main hospital to clinic 1. Each pathway changes at least one of these rows from the other time paths and the logic of these time paths are crucial in the patient flow and rerouting of patients after their clinical visits.

All clinics are structured the same way in the decentralized model. When a patient leaves their clinic, they have a ten percent chance of having another appointment in one of the other clinics. If they do, they head to this node and are redirected to their next clinic. The pathways were not shown in the Overview as they would have obscured the nodes and other parts of the model. clinical view as seen in Figure 15 which shows how Clinic 1 is modeled.

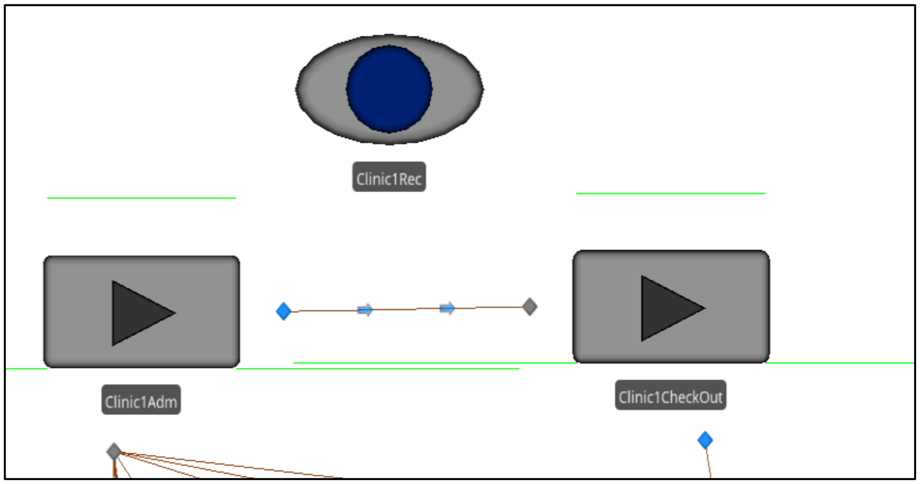

Figure 15: Example of a Clinic in the Decentralized Model

While Figure 15 only shows Clinic 1, this same structure is used for all clinics. It is comprised of three main parts; the check-in process (referred to as Clinic1Adm), the check-out process (Clinic1CheckOut), and the receptionist resource (referred to as Clinic1Rec). The receptionist resource references a specific table similar to Table 1, which makes changing the capacity of a clinic easy to do. The resource is used whenever there is a patient available for processing at either station. Clinic1Adm has the steps seen in Figure 18 from greeting the patient to asking the patient to sit down. Once this is concluded the patient goes on the time path between Clinic1Adm and Clinic1CheckOut. The Time path represents the patient's visit time at that clinic, and once the patient is done they can either start the check-out process if a receptionist is free or wait in line until one becomes available. An example of this is shown in Figure 16.

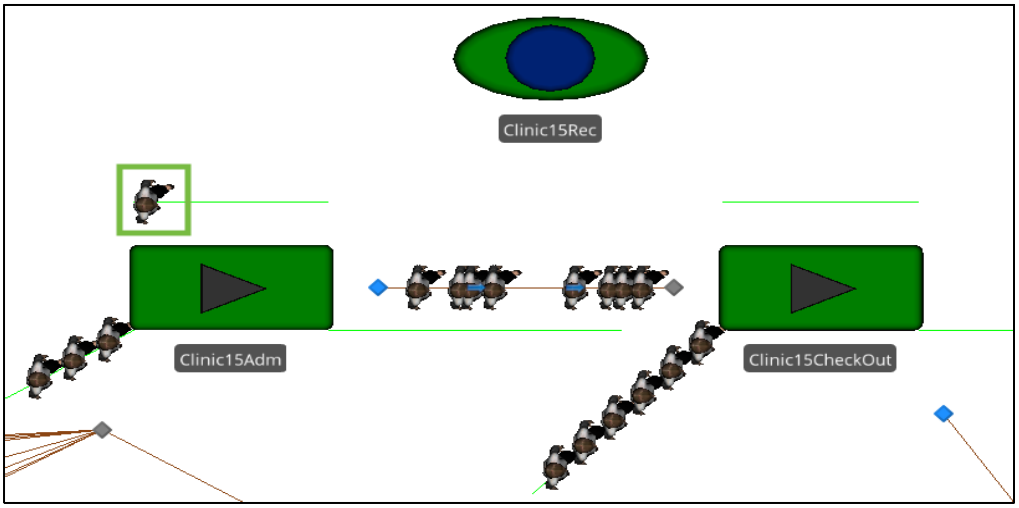

Figure 16: Snapshot of a Clinic Midway through Run

Figure 16 shows Clinic 15 which only has one receptionist, during one of its busier hours. The patient in the green box is the one being helped by the sole receptionist and three other patients wait in line at Clinic15Adm and six patients wait in line at Clinic15CheckOut. Several patients are at different stages of their clinical visit, and do not necessarily leave the time path at the same time. If one patient is assigned a 64-minute visit they will finish before a patient who was assigned a 112-minute visit even though the second patient completed check-in a few minutes before the first patient.

Once the Check-out process is complete, there is an additional add-on process that all patients go through. The rerouting process determines whether or not the patient leaves or has another appointment, and the likelihood for that choice is in the multiple appointment value in Figure 17. 90% of patients will not have another appointment and will be given a value of False after that decision step in Figure 17. The set node step then sends the patient directly from their clinic's check out server to the sink in the model. Once the patient reaches the sink their overall times are recorded and they exit the model.

If they do have another appointment they then are assigned a new clinic by reading a clinical mixture table to determine the likelihood of going to each clinic. Each clinic has a different likelihood of being selected, but the third column sets the likelihood to 0 if that is the clinic the patient is currently in. This way no patient is in a self-repeating loop of exiting one clinic only to return to it again, as that scenario is not likely to occur in real-life. There is a chance if a patient has more than 2 visits of then repeating a clinic they have visited before, but the likelihood of this occurring is very low and they will never be assigned the clinic they just exited so the possibility of having a preliminary appointment at one clinic, visiting another clinic, and returning to the first clinic is possible if unlikely.

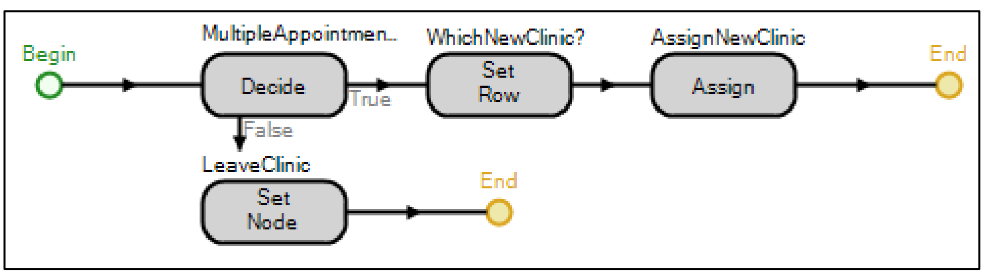

Figure 17: Rerouting Add-On Process

As the processes and logic are standardized for all the clinics in the model, each clinic has this same structure, independent of the number of clinics. To add a clinic would only require copying the three items and then changing the receptionist resource to reference the correct number of patients for the new clinic. The admission and check-out servers require no alterations except for name changes if they are copied for a new clinic and as each item has the previously shown add-on processes that reference the tables, making changes to a value in the table will apply for all the clinics in the model making changes easier and quicker to perform. A new row would have to be added in the Clinic Mix Table and the mixtures may change due to the new clinic. The hourly mixture table would have to be altered as well to give the percentages of patients who are assigned to the new clinic for each hour.

Adding in a new clinic also has a few more difficult steps in implementing the clinic into the layout. If the clinic is on a new floor that floor will have to be added into the model along with any lower floors for context. For example, the main hospital has 7 floors currently modeled and if the new model is on the 9th floor both the 8th and 9th floors have to be put into the model. As the layouts for these floors are abstract due to the difficulties in obtaining measurements by covid-19, this is not a largely time-consuming process. The more important change to the model is every new floor that has a clinic in it must have a floor node as shown in Figure 18.

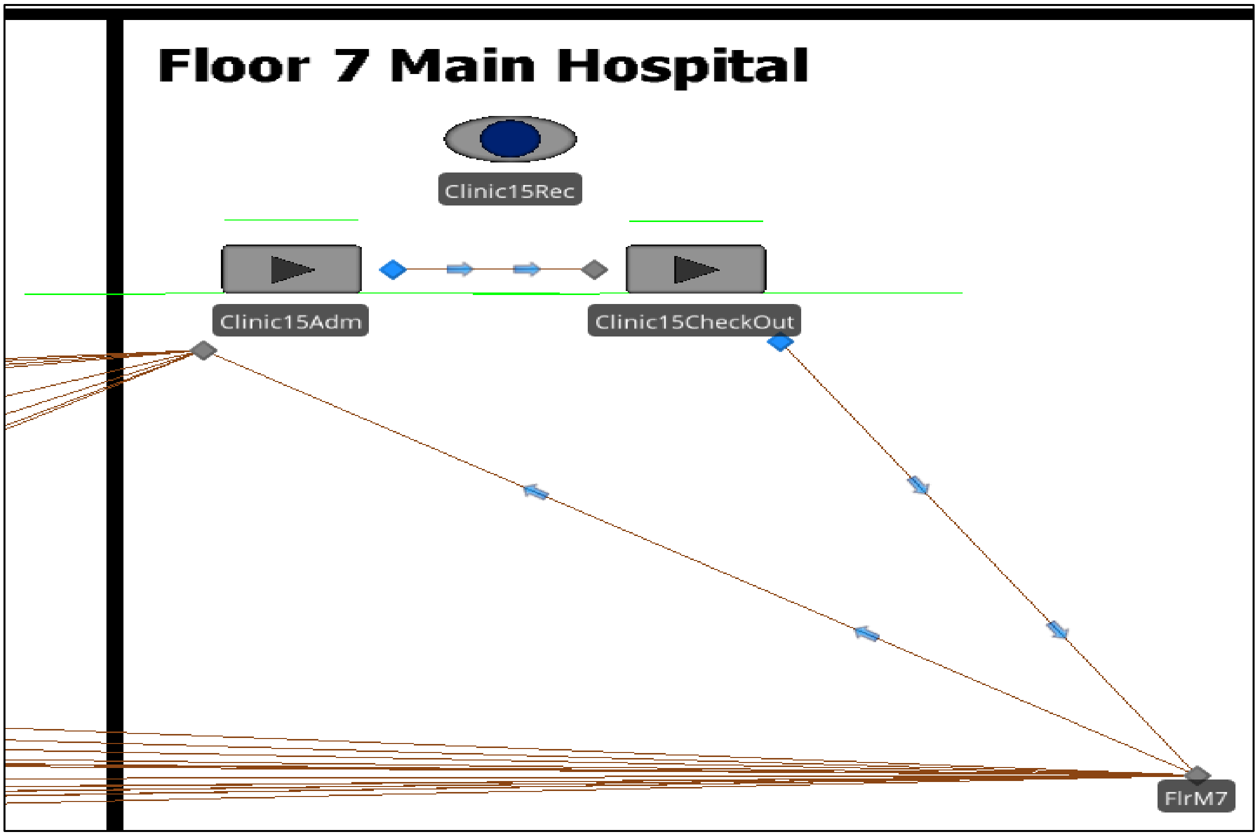

Figure 18: Example of a Clinic and a Floor Node

Each clinic has a connection to its floor's central node, in cases like the first floor of the main hospital all three clinics there have connections to the same node. These nodes serve as the sorting tool of the model to make sure that patients are going to the clinics they are assigned to with the correct travel time. The connection from Clinic15CheckOut to FlrM7 can be skipped if the patient does not have another appointment, so only a small number of patients travel to these nodes. If the patient leaves the facilities they are sent directly to the sink, and so there is no pathway shown in Figure 18 for leaving the facilities. If a patient is assigned to a new clinic they head to their floor's node. The node has as many time paths as there are clinics, in the current state being modeled there are 16 clinics. The node has a pathway to all clinics including ones on the same floor. As there are nine floors with clinics that are modeled, each clinic has 9 paths from the floor nodes to the check-in station.

To add a new clinic in an existing floor would require connecting the check-out station to the floor's node and connecting all 9 floor nodes to the new clinic with the correct times. Adding a new clinic in a new floor is a more intensive process as it requires a new floor node to be created. That node must then have pathways built to all clinics with the correct selection weight criteria to make sure patients are going to their assigned clinic, as well as the travel time between clinics. The other nodes would also have to create a new pathway from the floor the nodes are into the new clinic. This means adding a new clinic in an existing floor involves only adding a pathway to the new clinic for each floor node, while a new clinic in a new floor involves creating a new node and adding pathways to all clinics along to the pathways made from each floor node to the new clinic. Removing clinics is generally easier as deleting a node removes all pathways linked to it.

The centralized model shares many similarities to the decentralized model with two key differences, all patients must first go to the central admission location and the process for check-in from the decentralized model has been split between the central admission location and the clinics. Structurally, patients still arrive in the same arrival rate tables as before in the main lobby. The central admission location is considered only feasible in the lobby of the main hospital so other layout alternatives were considered out of scope for this model. The patients do have to travel to the central admission location so travel time is accrued, and the exact staffing of the central admission location is currently unknown. Therefore, the number of receptionists was kept as a placeholder value, and experiments were run to discover the optimal resource number. Figure 19 shows the placement of the central admission location on the first floor of the main hospital. Unlike the other clinics, the central admission location only has the check-in process and so there is no visit time or check-out process time afterward. Once the patient completes the central check-in process they are sent to the main hospital's first floor node and then redirected to their clinical destination.

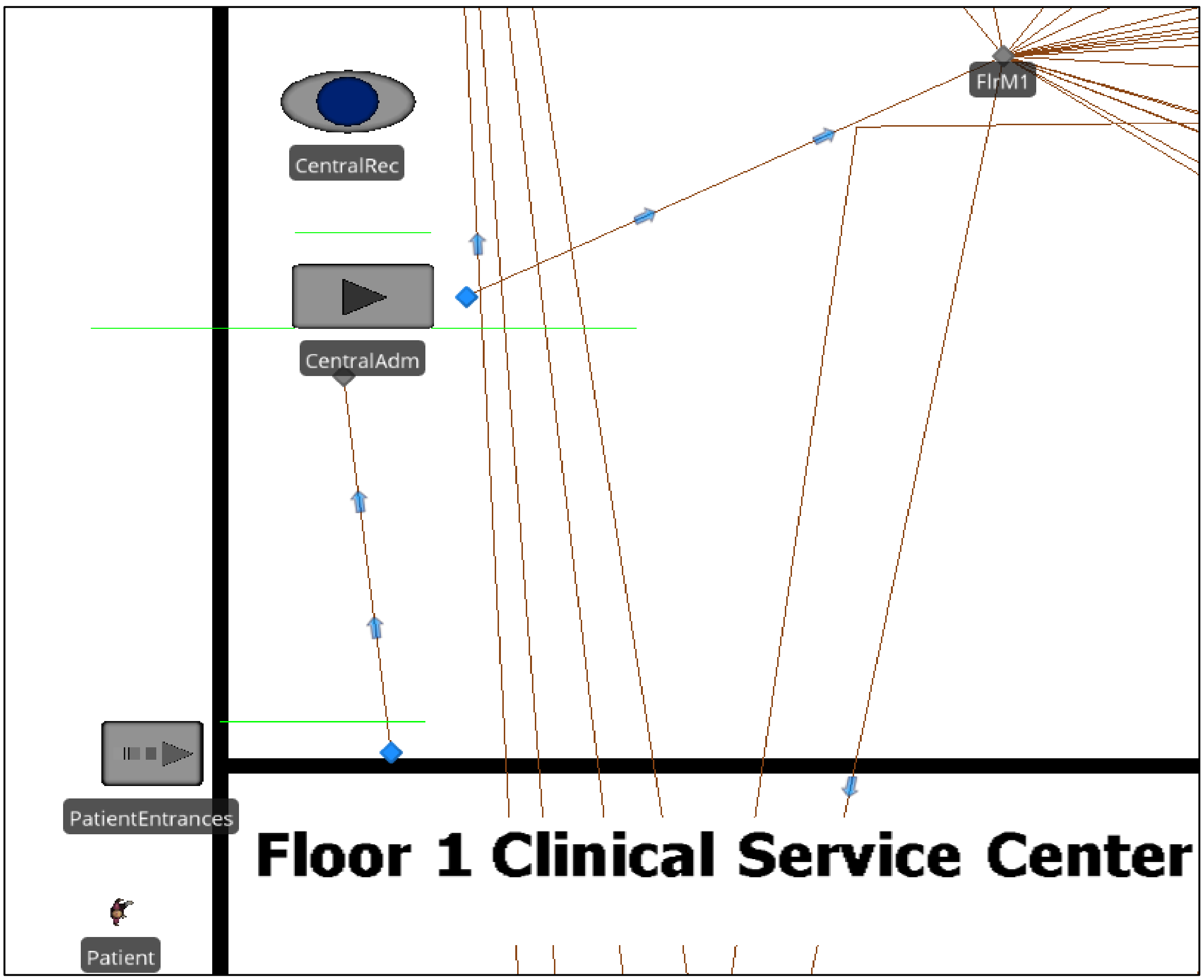

Figure 19: Central Admission Location in Centralized Model

The steps performed at the central admission location covers the majority of the steps from the decentralized model's check-in process. These processes were always modeled using add-on processes for both the decentralized and centralized models. This allows for changes in a singular step's time to be done in the add-on process and be applied to all clinics instead of individually changing the time for each clinic which greatly increases the chance of human error and the time associated with changes. These add-on processes also incorporate decisions in the check-in and check-out processes, which account for different process times dependent on the result of the decisions.

Overall, the rest of the centralized model functions exactly the same. The visit time and check out processes remain as is, and the rerouting logic and mixtures are the same. In no scenario does a patient have to go back to the central admission location. Therefore, the steps for adding or removing a clinic are exactly the same as the decentralized clinic.

4.2.4 Simulation Model Outputs

The primary metrics being recorded are the number of patients overall as well as the average number of patients at each clinic, the average wait times and process times for both check-in and check-out time, the maximum wait times for each clinic, and the overall throughput of each clinic. As processes are standardized this means that if all clinic mixture and staffing levels were equal, we would expect non-statistically significant differences between clinic wait times.

To account for multiple appointment patients, an add-on process was created that starts recording time once the patient enters a node and stops the time before they begin the check-in process. This allows both the travel time to the clinic and the wait time at the clinic check-in to be recorded. Patients with multiple appointments will leave their clinic's check-out station and head directly to the floor's node and start the timer again. Then, when they are finally serviced at the next clinic's check-in station, their time is recorded and added to their previous time. This accumulated time is considered the patient's total wait time. While the clinic wait time is a very good metric for staffing level compared to the clinic's hourly mixture and arrival rate, the patient wait time is a better indicator of the quality of care for the patients.

The metrics gathered in the outputs of the models differ slightly between systems, though most metrics gathered are the same with the key exception of wait time. Throughput, especially the ratio of patients who left the system compared to the number of patients who entered, is a metric gathered by the models. Wait time is still calculated similarily with the addition of both the travel time and waiting time to the central admission location being collected as well. If patient wait time at each clinic decreased slightly but increased in total due to the central admission location step then this would negatively harm patient satisfaction. As the centralized model has an additional step it would indicate that patient wait time may increase unless clinical wait time experiences a significant enough decrease compared to the decentralized system. For all waiting metrics, whether or not the times are acceptable depends on the healthcare organization, most likely patients will want times for less than 30 minutes.

4.2.5 Simulation Model Experiment

Now that the general models have been created, experiments have been planned to test the conditions in which a centralized system is better than a decentralized system and vice-versa. The primary conditions being tested are different rates of patient arrivals, varying mixture of patients per clinic, a range of percentages of multiple-appointment patients, shorter and longer travel times between clinics, and the number of clinics in the system.

5 Experimental Runs and Model Outputs

When comparing the centralized and decentralized systems, different scenarios must be tested on each to determine their relative strengths and weaknesses. From the literature review, there were some key possible scenarios to test, primarily the number of patients who visited each day and the number of clinics. Alongside that are differences between clinics, if some are more visited than others by a large amount. As discussed with Organization A, the effect on the different systems on multiple appointment patients is a key factor for deciding which system should be put into place for the organization. As wait time is a crucial factor that is also dependent on travel time, an increase of travel time between experiments can show how effective each system for more distant clinics. However, before any of these different scenarios could be tested, the staffing number for the centralized model must be determined in order to create a fair comparison between the two models. Once staffing is determined, the general experiments can be run to find the characteristics under which each system performs better than the other, and this information can then be applied to the validation models from Organization A.

5.1 Determining Staffing for Centralized Model

To determine the best-suited system for Organization A as well as the amount to use for the general experiments, first we must determine the exact amount of staffing for the clinics and the central admission location in the centralized model. This process was first done by running the centralized model at the average arrival rate and with a ten percent chance for multiple appointment patients, where the capacity for each resource was set to 999.

While this staffing would be physically impossible, the model only calls upon resources when needed, so this approach shows both the average amount of resources called for and the maximum amount without any limitations. This gives both an upper and lower range for the number of receptionists for each clinic that should be tested in the model. As the base results of the current state decentralized clinic are known and were told to be used as the benchmark by Organization A, the goal of this run was to learn the ranges of receptionists to try in the model to find a staffing level that matches the clinic wait time and patient wait time from the decentralized model's results. It is unlikely that any results will be completely equal as the central admission location and the new clinical check-in make significant changes to both the clinic wait time and the patient wait time, but aiming for an equal or less than the amount for both metrics with the centralized model should be aimed for before the general experiments and later validation experiments are ran. The results of this run are seen in Table 5.

Table 5: Centralized Model Receptionist Numbers

	Units Utilized Average	Units Utilized Maximum	Min Rec	Max Rec
Clinic1Rec	0.18	2.70	1	3
Clinic2Rec	0.37	4.07	1	5
Clinic3Rec	0.22	3.02	1	4
Clinic4Rec	0.43	4.19	1	5
Clinic5Rec	0.43	4.16	1	5
Clinic6Rec	0.40	4.06	1	5
Clinic7Rec	0.56	4.79	1	5
Clinic8Rec	0.33	3.84	1	4
Clinic9Rec	0.44	4.34	1	5
Clinic10Rec	0.26	3.24	1	4
Clinic11Rec	0.76	5.59	1	6
Clinic12Rec	0.24	3.21	1	4
Clinic13Rec	0.12	2.37	1	3
Clinic14Rec	0.16	2.69	1	3
Clinic15Rec	0.14	2.50	1	3
Clinic16Rec	0.13	2.46	1	3
CentralRec	2.77	13.25	2	14

The decentralized model with the current state staffing levels was ran over 300 replications to make sure that no single replication was skewed towards the upper or lower limit of the arrival rate, travel times, process times, or clinical mixtures. The high number of runs gives a greater vision on how the clinics function overall, and the results of the run are shown in Table 6 with all times in terms of minutes.

Table 6: Decentralized Current Staffing Results

Clinics	Receptionists	Avg. Check-In Wait Time	Max Check-In Wait Time	Avg. Check-In Processing Time	Avg. Check Out Wait Time	Max Check Out Wait Time	Avg. Check-Out Process Time	# Entered Check-In	# Left Check-Out
1	2	0.20	3.20	4.06	0.21	3.23	3.64	30.40	30.11
2	4	0.03	1.03	4.08	0.04	1.14	3.57	60.32	59.80
3	2	0.28	4.21	4.10	0.27	4.32	3.57	36.26	35.90
4	4	0.04	1.36	4.08	0.05	1.59	3.65	72.74	72.09
5	4	0.04	1.34	4.10	0.04	1.35	3.58	70.41	69.65
6	3	0.20	3.94	4.10	0.22	4.16	3.54	67.32	66.57
7	4	0.10	2.76	4.10	0.10	2.95	3.61	94.94	94.01
8	4	0.02	0.79	4.10	0.02	0.83	3.56	57.14	56.46
9	3	0.30	4.89	4.08	0.31	5.11	3.58	73.06	72.29
10	2	0.50	6.11	4.05	0.53	6.67	3.61	44.00	43.55
11	3	1.38	11.20	4.09	1.47	11.62	3.56	128.51	126.15
12	2	0.46	5.65	4.10	0.49	6.02	3.55	40.43	40.04
13	1	1.65	11.10	4.10	1.70	11.47	3.60	19.28	19.10
14	1	2.52	15.78	4.12	2.83	17.25	3.52	26.59	26.28
15	1	2.49	15.27	4.06	2.64	15.62	3.51	23.74	23.55
16	1	2.03	13.38	4.09	2.33	14.71	3.59	22.58	22.39

The results would indicate that either clinics 2, 4, 5, 7, and 8 are overstaffed or that clinics 13 through 16 are understaffed. As mentioned previously, there are certain tasks receptionists perform that are not captured in the model, usually when they have no demand for incoming patients. For example, if in one of the 4 receptionists clinics only 3 receptionists are needed during most times, the fourth receptionist can spend this time calling no-show patients or doing other administrative or operational tasks. Therefore, we can assume these results are more likely to show understaffing than they are to show overstaffing and that the results from the decentralized current state run can be used as a benchmark as stated by Organization A.

In summary of table 6, the average waiting time at the check-in process was 0.77 minutes, with the average maximum check-in time being 6.38 minutes. The total of all the average check-in wait times across the clinics was 12.25 minutes while the summation of all the maximum check-in wait times across the clinics is 102.01 minutes. The times for the check-out process were similar but slightly increased. The average wait time was 0.83 minutes while the average maximum wait time was 6.75 minutes. The total wait time was 13.27 minutes and the summation of the maximum check-out wait times was 108.04. As stated before this is not all-inclusive of the tasks the decentralized staff had to perform, and the current staffing level is assumed to be as optimal as possible including those steps. Therefore, changing the staffing of the decentralized model was outside of the scope, and the metrics above were used as a benchmark for the centralized model. The differences between the clinics show the significance of the staffing numbers, as the waiting time decreases dramatically from having 1 receptionist to 2 receptionists, though the effect then minimizes with the primary change being the reduction in the maximum wait time, which was only greater than 10 minutes for 5 clinics, four of which only had 1 receptionist while the last has the highest demand of all clinics and requires more capacity than the average clinic.

To determine the staffing level for the centralized admission model to be an accurate comparison against the decentralized model, the number of receptionists for the central admission location, and the number of receptionists per clinic. As the central admission location is the first step for all patients and there is no rerouting of patients back to the central admission location once they have completed the central check-in process, the number of receptionists for the central admission location is independent of the other clinics. All of the clinics could increase their capacity to 500 receptionists but that would not affect on the central admission location. This does not work in reverse as clinics are waiting for patients to go through the central check-in process so delays in the central admission location can compound with the clinics.

Since it was paramount to determine the staffing in the central admission location clinic first, multiple experiments were ran to find the optimal number of receptionists needed. In these experiments, all other clinics were set to a staffing level of 1, though the primary metrics being observed were those of the central admission location so the staffing of the other clinics could have been any positive whole number. From the results in Table 5, the first experiment was set to the minimum number of receptionists for all clinics, and so the central admission location only had 2 receptionists. This value was increased one at a time from experiment to experiment. As there is no direct comparison to the central admission location in the decentralized model, choosing the exact correct time is difficult, so reaching a near optimal waiting time or a plateau where adding new receptionists adds no value was the primary goal of the experiments. The results shown in Figure 20 show the problems of understaffing the central admission clinic as even the average time for 4 receptionists or less is greater than 30 minutes. As this is also the first step in the process those average wait times would result in a strong negative patient experience. It is only at the 5 receptionist level that the central admission location becomes feasible without hurting the patient's experience. However, the results do show a drastic reduction for each receptionist added. The results for the 5 receptionists are not great, especially when considering that these are the results for the average arrival rate. Having 6 or 7 receptionists would appear to be the best approach. On average there is little difference between the two, though having 7 patients would be better for maximum time scenarios.

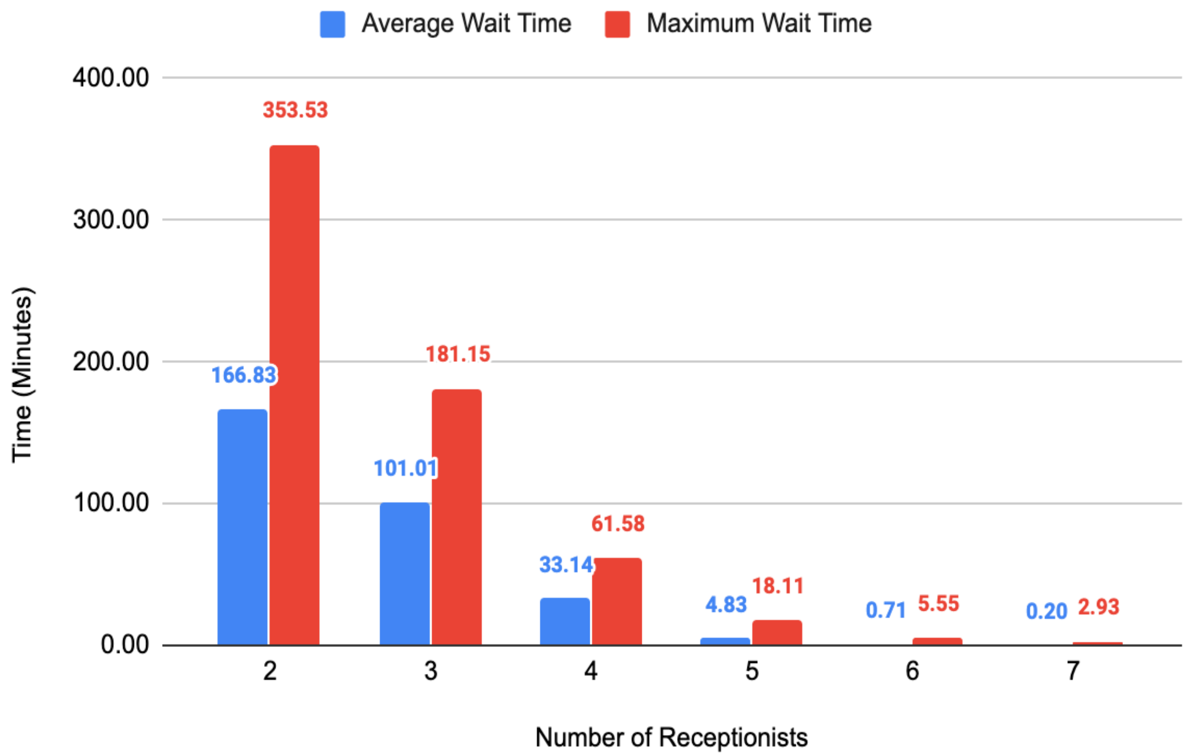

Figure 20: Central Admission Location Staffing Levels

For the centralized clinic, it is assumed that 6 receptionists would be a suitable level though some organizations would choose the 7-receptionist level in this scenario. While 6 receptionists seem to be the best comparison for the centralized admission location, the number of receptionists per clinic has also appeared to change. Figure 21 shows the difference in the combined check-in and check-out times for each system depending on the number of receptionists per clinic. The results show having one receptionist is more efficient than in the decentralized model with the overall time being around a fourth of the wait time for one receptionist clinics in the decentralized model. However, this is still an average of about 6 minutes for both check-in and check-out for the centralized clinic during an average arrival rate, full times are in tables A2 and A3 in the appendix.

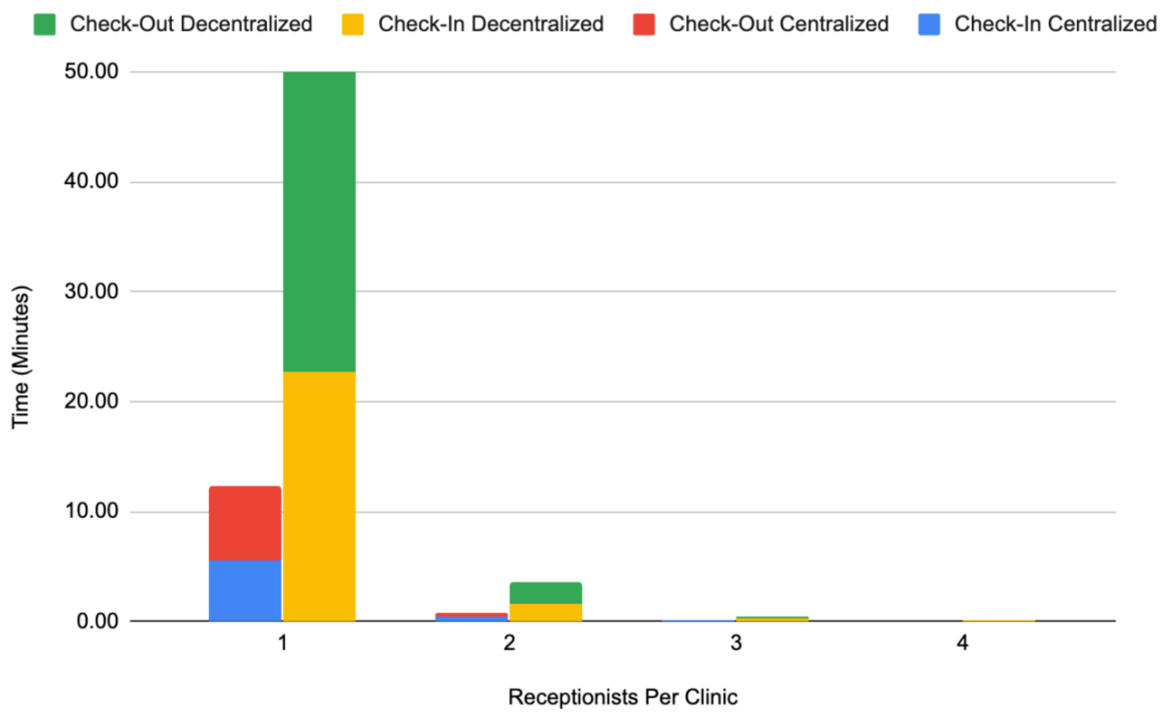

Figure 21: Average Clinic Waiting Time vs Receptionists per Clinic

While one could consider one receptionist for the centralized model acceptable, it is also important to look at the maximum waiting times that a patient as patients who experience a longer wait time are more likely to have a negative experience. Figure 22 shows the combined maximum waiting time for both the centralized and decentralized systems. Once again, having one receptionist falls into around the halfway point of performance between the 1-receptionist clinics and 2-receptionist clinics in the decentralized. Due to the high combined maximum wait time, it appears that 1 receptionist may not be suitable, especially if demand is greater than average.

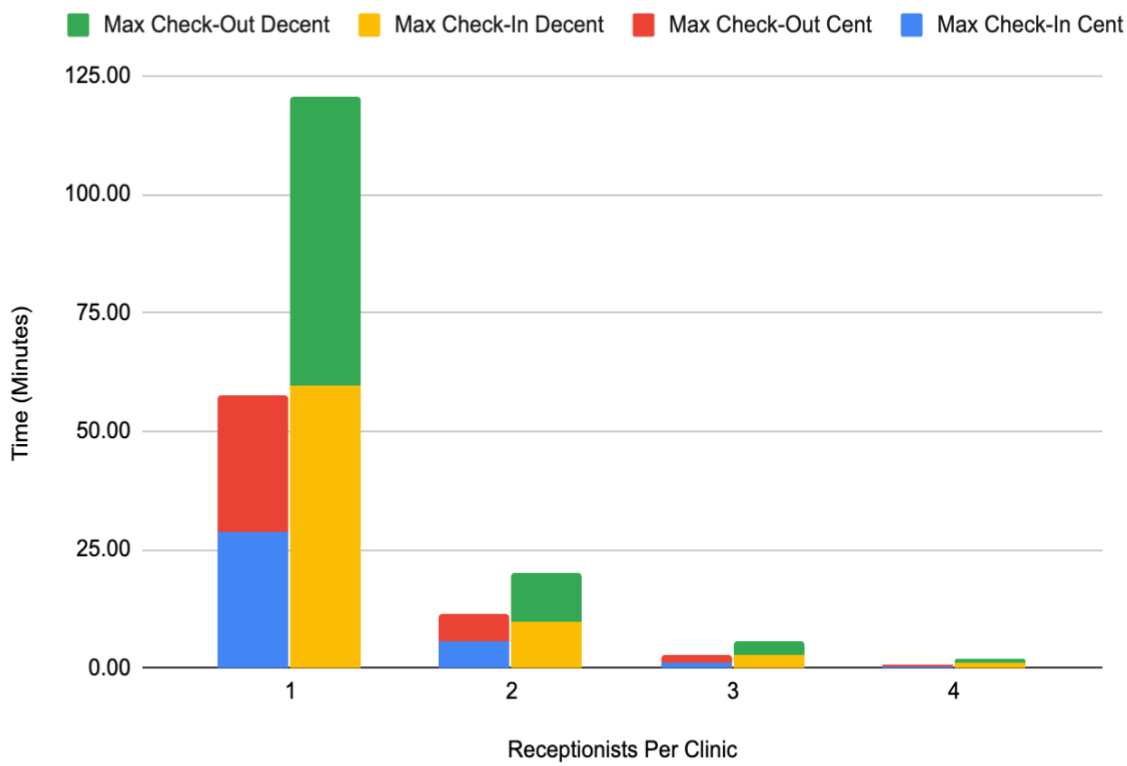

Figure 22: Maximum Clinic Waiting Time vs Receptionists per Clinic

Determining whether to choose 1 or 2 receptionists for the centralized clinics also involves creating a fair comparison with the decentralized model. The times for both Figure 21 and Figure 22 are averages across all clinics and some clinics have a much larger demand than other clinics. Therefore, the best combination would be to use 1 receptionist when possible but to increase the staffing at other clinics when needed. This shows that in general, a centralized system can drastically reduce the time spent at each clinic for the check-in process and the associated wait time allowing for fewer receptionists to be needed at each clinic. However, the reduction seen in Figure 21 and Figure 22 can bring into question the usability of this change as the improved state may still result in too long wait times for the same number of receptionists. Therefore, while there is a significant decrease in wait time per receptionist, the usability of this change is dependent on the capacity needs of the organization.

While the decentralized system has longer wait times for their receptionists on average, the current staffing levels have resulted in low overall wait times and maximum wait times, as many clinics have 3 or 4 receptionists, as shown in Table 7. Staffing levels were increased by one receptionist for the clinic with the longest wait time until the results were similar to the middle column in Table 7. As shown in Figures 21 and 22, one receptionist was more effective, but to reach comparable metrics to the current state a second receptionist had to be added in most clinics. When adding the second receptionist the largest impact was on the overall wait time, the maximum wait times generally remained greater than the decentralized current state. As there were many possible configurations for a centralized clinic that could be used with some having a closer maximum wait time to the current state, and others with a closer average wait time. To decide which staffing level is the closest fit, both times were used with an emphasis on the average wait time, as it is a better metric to judge compatibility than the average maximum wait times across all clinics which can be increased due to a single clinic or due to the variation in runs of the model. Two staffing levels appeared to be the closest on average to the current state; Centralized Staff 1 has 6 receptionists in the central admission location, 2 receptionists for clinics 2 through 12, and 1 receptionist for the remaining clinics. Centralized Staff 2 has the exact same staffing levels, except Clinic 1 now has 2 receptionists and Clinic 11 now has 3 receptionists as it has the highest demand of all clinics.

Table 7: Centralized Staffing Comparison

		Centralized - Staff 1	Decentralized - CS	Centralized - Staff 2
Check-In Wait Time	Average	0.76	0.77	0.55
	Avg Max	9.15	6.38	7.42
	Sum Avg	12.12	12.25	8.80
	Sum Max	146.46	102.01	118.72
Check-Out Wait Time	Average	.91	0.83	0.66
	Avg Max	9.44	6.75	7.72
	Sum Avg	14.55	13.27	10.56
	Sum Max	150.99	108.04	123.48

While Centralized Staff 1 has very similar average times with the current state, the maximum times are usually fifty percent higher than the current state. Centralized Staff 2 has average wait times around 2/3rds or 3/4ths of the current state. The times for each clinic are in Table A4 for Centralized Staff 1 and Table A5 for Centralized Staff 2 in the appendix. While the maximum times are still greater as well, the difference is not as great as the difference between Centralized Staff 1 and the decentralized system. Different staffing levels that minimized the maximum wait time to reach the current state levels caused the average times to become far shorter, so while there is no perfect comparison between the two systems, the two staffing levels in Table 7 are two of the closest. Centralized Staff 2 was chosen as while the averages are shorter, the maximum times are greater than the current state and so it is more balanced than Staff 1 which will on average perform worse than the current state. Centralized Staff 2 also only requires 35 receptionists including the 6 central admission location receptionists compared to the 41 receptionists in the decentralized model. If the organization is unworried about the maximum wait times and chooses Centralized Staff 1 then the reduction in staffing is 8 receptionists. Either choice results in a significant reduction.

Now that the staffing for the centralized system has been determined and the two systems are comparable, the same experiments can be run on each system. To determine the characteristics that best suit each approach, multiple different scenarios were ran for each characteristic being altered from run to run.

The primary factors being considered was the effect of arrival volume, differences in clinical mixtures, the number of clinics, the number of multiple appointment clinics, and the travel time between clinics. Using the data from Organization A as the starting point for the experiments, each of the factors was changed to include multiple levels. Both systems were ran using the different levels for each factor to compare average and maximum clinical wait time, average and maximum patient wait time, and general throughput across the facilities. These three main metrics serve as the deciding factor in which system is best suited for each level of the factor being changed, showing overall what scenarios best suit each approach.

5.2 Arrival Rate Experiment

To begin with, five separate arrival rate tables were tested across the decentralized and centralized clinics in which the average amount of patients ranges from 50 percent and 25 percent lower and higher than the current average. As mentioned previously, both the number of patients per hour and patients per clinic depended on the total day's admission. On average this number is 779 patients, yet an increase of 50% brings this number to 1095 patients. These arrival rates table are seen in Table 3. As many clinical organizations experience a large variation in their arrival rates per day (as shown in the literature review) testing different volumes of arrivals is necessary to know if any system has a particular weakness towards peak days or is unsuited for lower demand.

For the experiment both systems were set to their staffing level, the current state staffing for the decentralized model and centralized staffing 2 for the centralized model, and the current levels of multiple appointment patients, travel time, and other factors previously mentioned. 500 replications were run for each arrival rate table, so 2500 replications were run for each system.

Once all runs were complete the two systems were first compared by throughput. The data from all runs are in Tables A6 and A7 in the appendix. Figure 23 shows that overall the throughput was the same, with the differences in the ratio of patients who left over patients who entered were caused by the variation in the models and not due to one system holding back more patients. Seeing how both had the expected ratio for throughput, as many patients are still in the model either in their clinical visit, or arriving at another appointment, the key result is there is no statistically significant difference between the two systems. However, while the amounts of patients who left may have been the same, the time they spent in the system waiting may have been radically different.

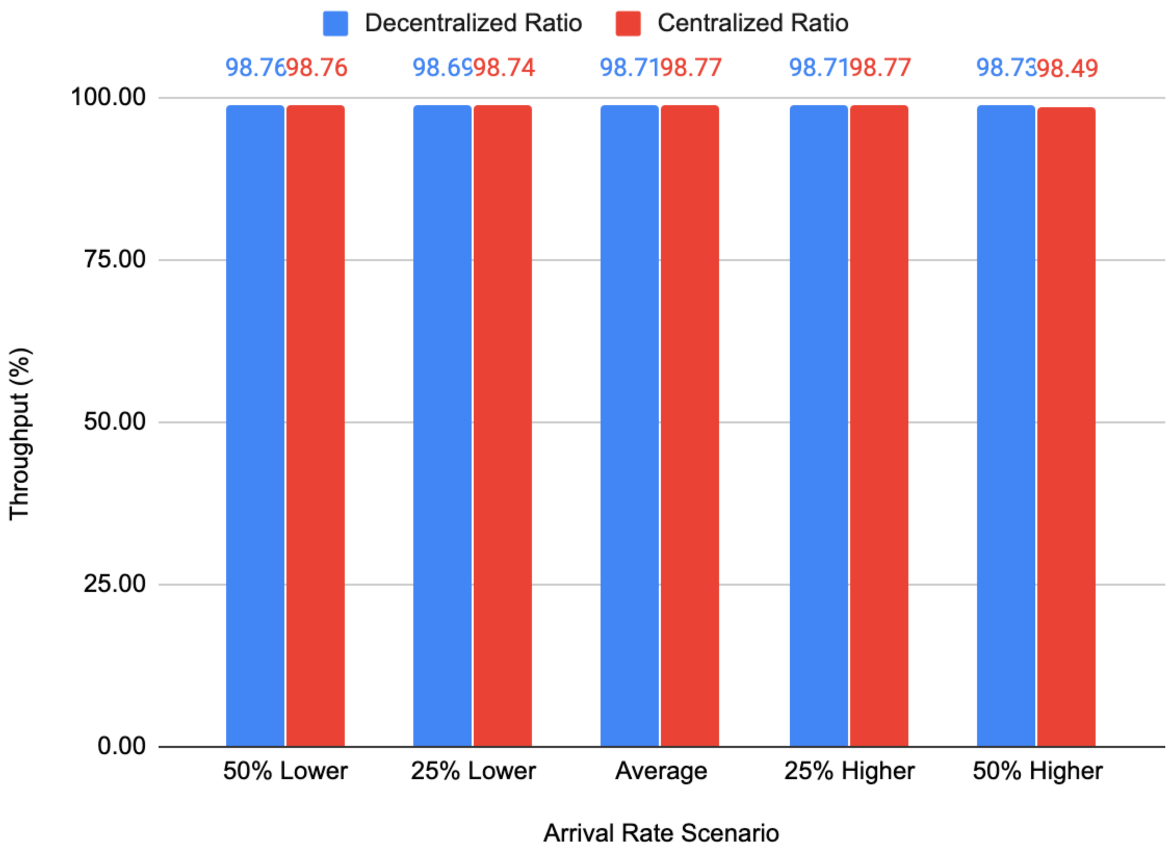

Figure 23: Ratio of Patients who Left over Patients who Arrived

As there are no significant throughput differences, the next metric examined was the difference in wait time for each clinic. At both the Check-In and Check-Out processes, patients must wait for a receptionist to be available, which takes longer if there are more patients already in the system. The wait time per clinic is a good indicator of the effect of the handoff procedure on the capacity needed for the clinics under the different arrival rates. As seen in Figure 24, the centralized clinics under the staffing level from Centralized Staff 2 have a smaller overall wait time for both the check-in and check-out processes. The decrease in time increases as the arrival rate increases. For both the 25% and 50% lower arrival rates the difference is minimal.

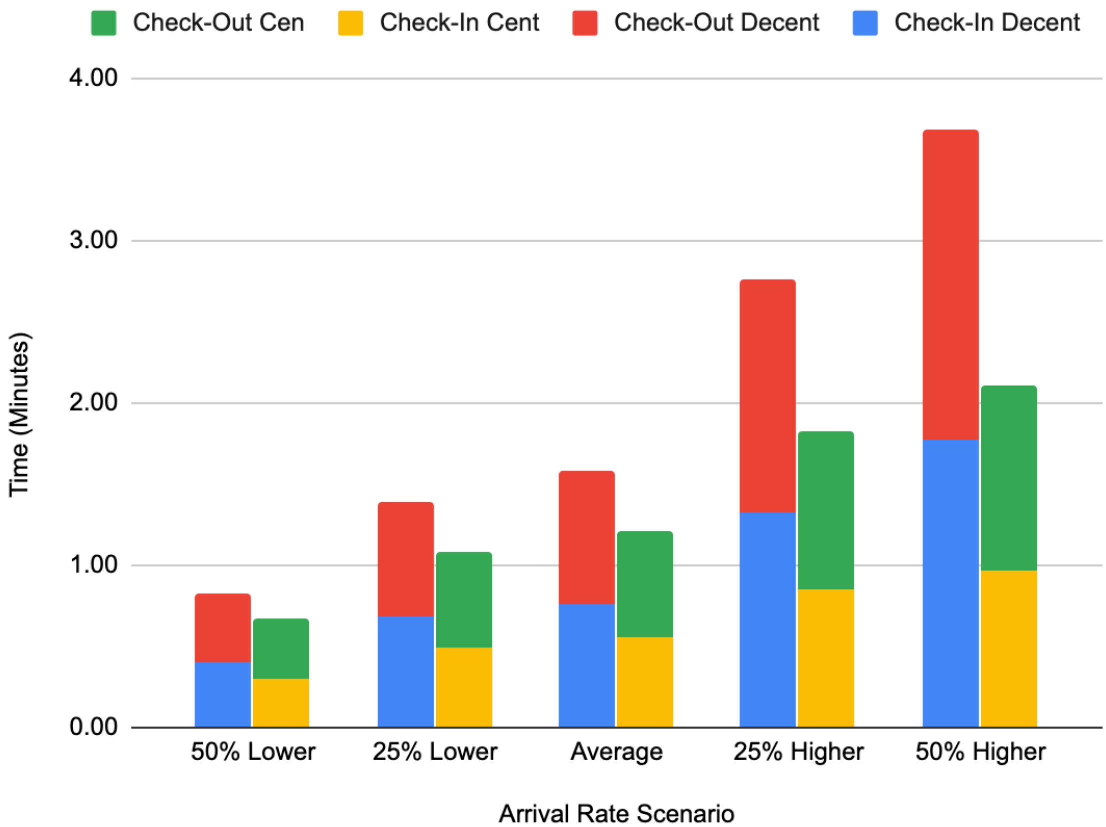

Figure 24: Average Wait Times for Different Rate Tables

While wait times per clinic did decrease in the centralized version across all rate tables, the maximum wait times for clinics increased in the centralized system. The differences are similar are usually in the range of one to two minutes which is greater than the usual difference in average wait times in Figure 24. However, it falls to the organization to decide on whether the average waiting time or the maximum waiting time is the more important metric. If there is no clear distinction for the organization, the matter may fall under a decision of patient wait time instead of the clinical wait time.

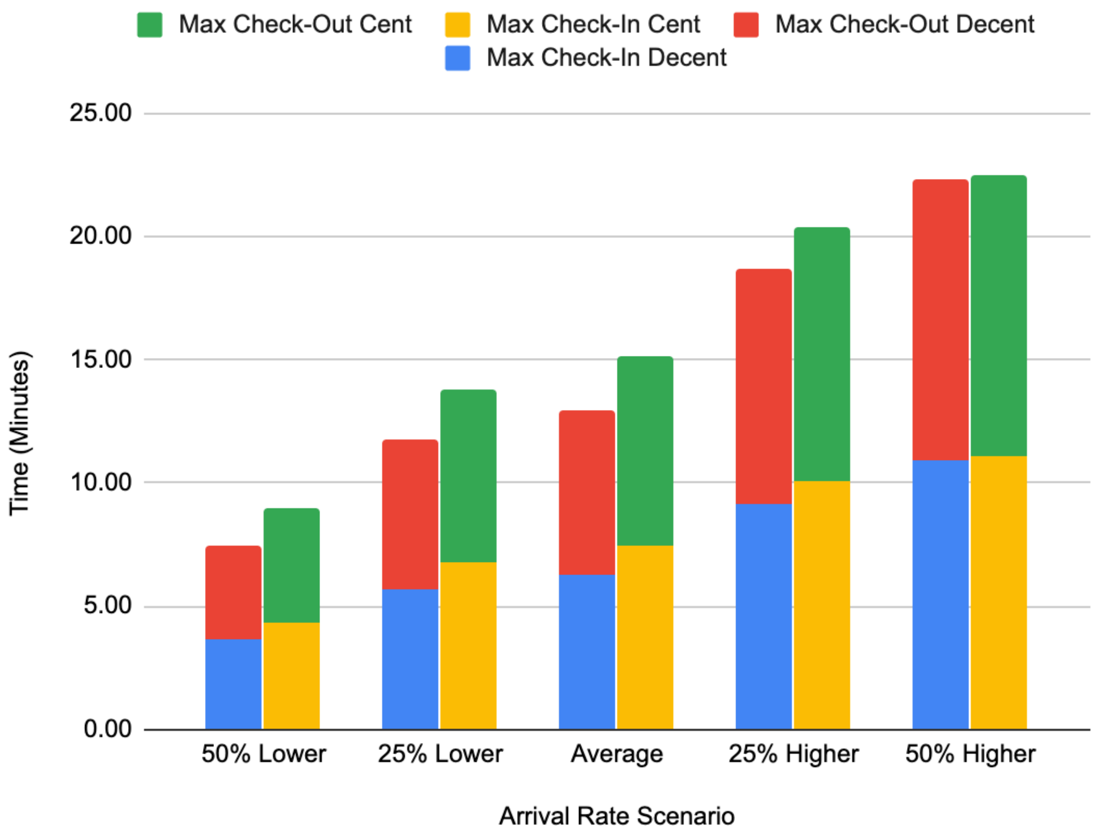

Figure 25: Maximum Wait Times for Different Rate Tables

For both the average and maximum wait times at the input buffers of the check-in and check-out clinics a 95 percent confidence interval. These can be seen in Tables A8 and A9 in the appendix. The results show that for the average clinic times, only the check-out wait times in the 25 percent lower and 50 percent lower were insignificantly different between the centralized and decentralized system. Figure 24 would seem to imply this as the check-in wait times are more vary more than the check-out wait times, and make the majority of the total time difference between the two systems in those scenarios. The reason why the check-in wait times are significantly different while the check-out times are most likely primarily due to the shorter check-in process time and the first come first serve prioritization scheme most likely slightly benefiting the check-in patients. However, while the check-out wait times were the only not significant differences in the two lessened arrival rate experiments, overall the confidence intervals between the two systems became closer, especially in the 50 percent lower arrival rate experiment. In that scenario, the gap between the confidence intervals was .02 minutes for average check-in wait times and .01 minutes for maximum check-in wait times.

While the reduced arrival rates generally saw the confidence intervals move closer together, the 25 percent higher and 50 percent higher arrival scenarios saw an increase in the difference in average times but also experiences the maximum wait times becoming closer between systems. For the 25 percent higher and 50 percent higher scenarios both the maximum check-in and check-out wait times had overlapping confidence intervals. Therefore, the only significant differences in terms of maximum clinic waiting time are for the average rate and reduced rate scenarios in which the decentralized model performed better than the centralized model.

The data previously seen covered all clinics with the exception of the central admission location for the centralized system. The central admission location had its wait times recorded separately. The staffing used in the centralized system quickly caused long wait times for the increased volume rate tables. The current level of 6 receptionists was not suited for the larger volume days as the average time skyrocketed to above 20 minutes for the 50% larger admission day. As an average time, this would most likely negatively hurt the patient's experience, especially as the central admission location is not their destination clinic. While in certain hours of the day the 6-receptionist central admission clinic can meet the demand of the higher days, overall it performs poorly and so a second setup was tried with an additional receptionist. The improvement in average wait times is shown in Figure 26.

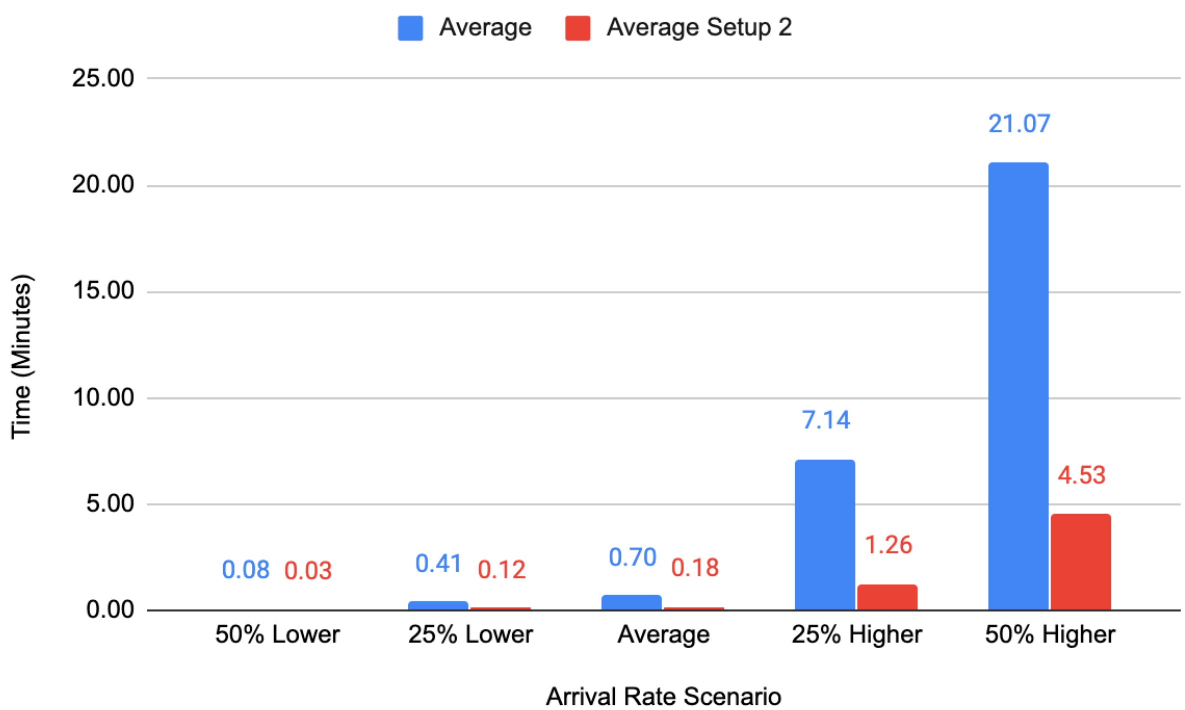

Figure 26: Central Admission Location Wait Times for Different Rate Tables

The central admission location is one of the more difficult locations to determine the staffing needs and can react in a volatile manner if the patient volume exceeds its capacity. While that was shown in the average wait time, the maximum wait times also show the drastic wait times for the high-volume days. The second setup does perform better, but Figure 27 shows that even that setup has a large maximum wait time for the 50 percent higher rate table. When the organization decides how many receptionists to use in their central admission clinic they will most likely either have to know their daily volume accurately or overstaff in case of unpredicted increases in arrivals. As the centralized clinic already has a reduced staff, adding an additional receptionist to the central admission location may be the best choice for an organization with high demand days.

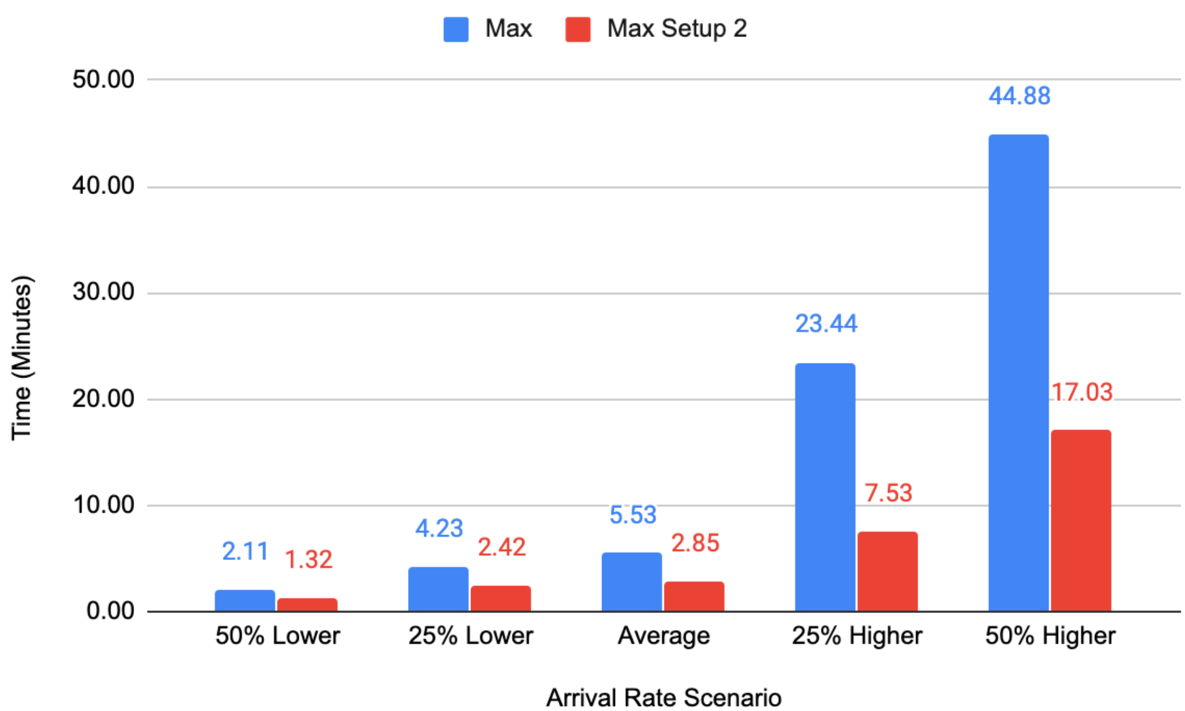

Figure 27: Maximum Central Admission Location Wait Times for Different Rate Tables

Process Times remained the same across the five scenarios, yet show a clear distinction between the two systems. In the decentralized model, the average time it takes a patient to go through the Check-In process is 4.09 minutes and the Check-Out process takes on average 3.59 minutes. In the centralized system, the Check-Out process remains the same and had an average of 3.61 minutes which is due to the variation internal to the process. Every clinic now performs the Handoff process which only takes 0.74 minutes on average, with the majority of the decentralized Check-In steps are now performed at the Central Admission Location in their Check-In process that usually takes 2.56 minutes. Combining those two processes which were originally the decentralized Check-In process gives an average time of 3.3 minutes.

While the time a patient waits at each clinic is important it is not all-inclusive of their total wait time. The time spent traveling as well as the time spent waiting to be attended by both the clinics and the central admission location are collected together. For the decentralized model, the shortest time would be only the time associated with traveling to the clinic and waiting for Check-In. If the patient had an additional appointment then the travel time to that clinic along with the waiting time of that clinic is added as well. This is the same for the centralized model with the exception that the travel time and waiting time of the central admission location are included as well. While the average and maximum clinic wait time is an important indicator of a system's performance, the patient wait time is a better metric for patient satisfaction and experience using the facility. Figure 28 shows for both systems the average rate table as the 1st scenario, and the 25% and 50% higher rate tables as scenarios 2 and 3 respectively. The average patient wait time is shown for the hour of their arrival. The remaining two scenarios were excluded as their times were very similar to the scenario 1 results of both models, but they can be seen in Table A6 for the decentralized scenarios and Table A7 for the centralized scenarios.

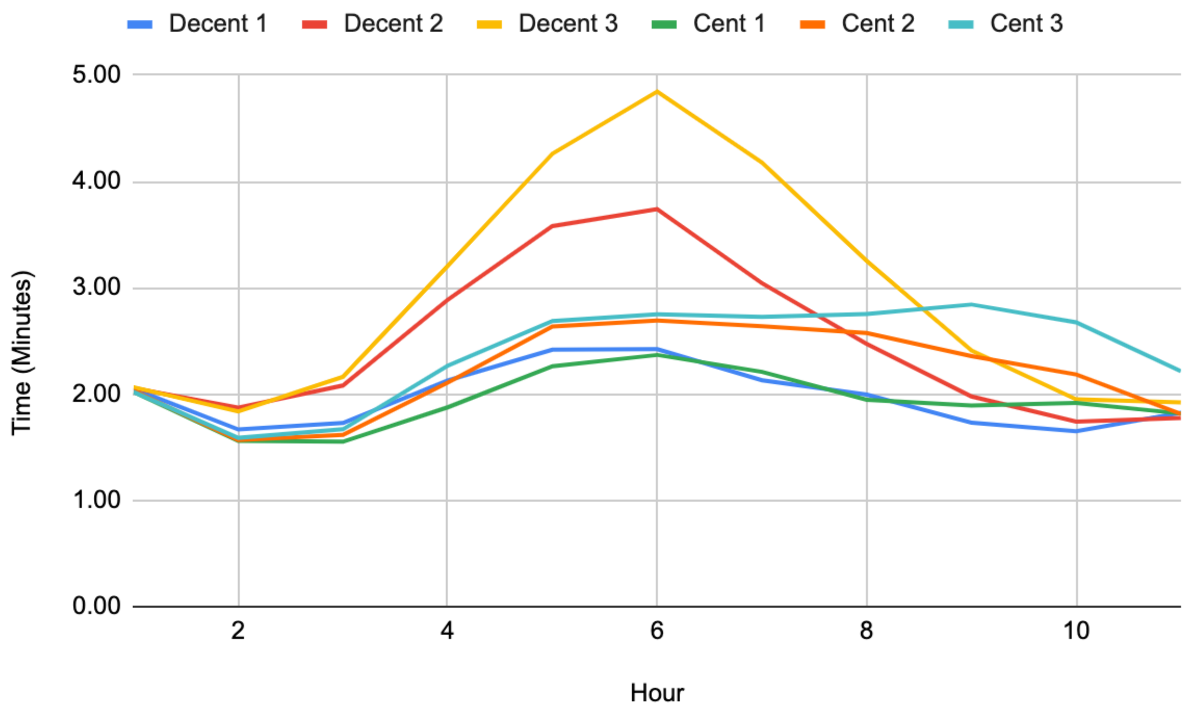

Figure 28: Average Patient Wait Time per Hour of Arrival

Wait Time per hour generally increases along with the hourly arrival of patients as clinics are both busier and more patients are more likely to become multi-appointment patients and influence the average patient wait time. While the hourly arrival rates all have a peak from 8 AM to 10 AM, which would correspond with hours 3 to 5, and another smaller spike at hour 8 at 1 PM, most of the results above show a non-stop growth at hour 3 to hour 6. The earlier spike has a delayed effect where patients who entered in hour 3 have similar patient wait times to those in the first two hours, but the delays caused extend past the initial peak into hour 6, which is one of if not the highest patient wait time for the six scenarios. Figure 29 shows the maximum patient waiting time per hour which unlike the average time shows a steeper ascent at first and a more gradual parabolic curve of the patient wait time. For both Figure 28 and Figure 29 the highest times were for the decentralized scenarios of 50% more arrivals and 25% more arrivals, with the centralized results for those scenarios as the next highest, though the centralized system has the highest patient wait times from hour 9 onwards. This is most likely due to the centralized admission location having a large delay as these results have only 6 receptionists at the location. Finally, the two average rate scenarios are at the fastest, with the centralized version being slightly faster.

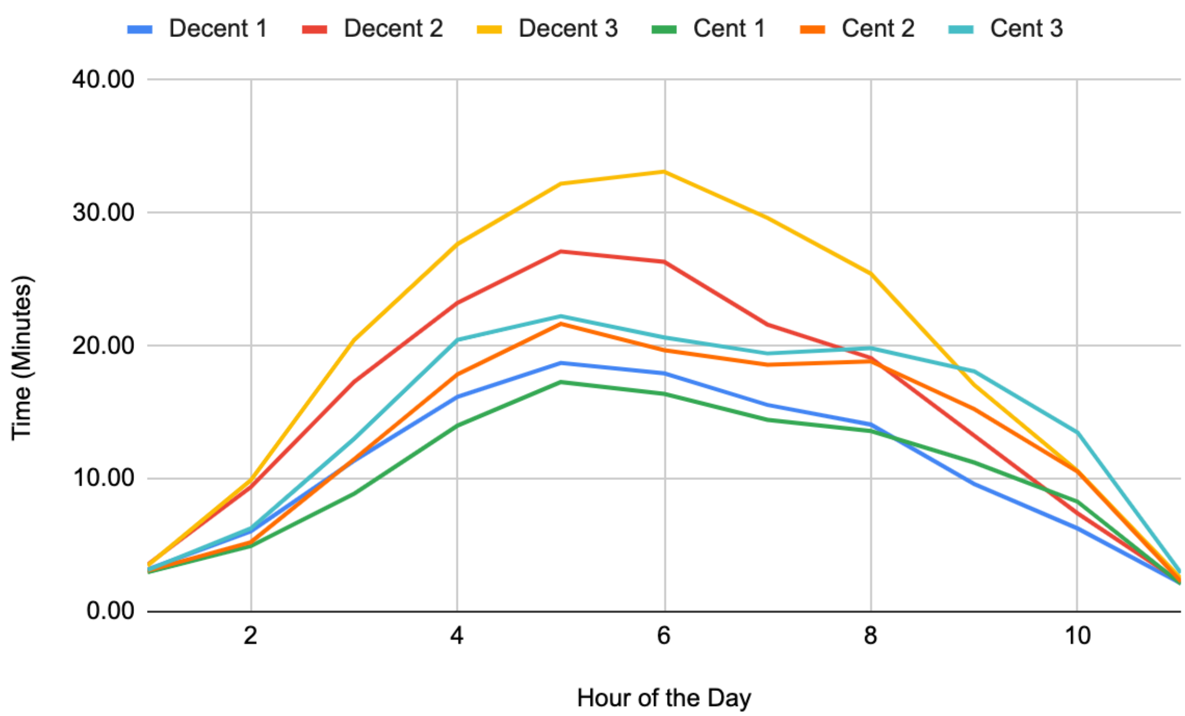

Figure 29: Maximum Patient Wait Time per Hour of Arrival

Not all differences in patient wait time were significant as shown in figures 28 and 29. For both the average and maximum patient wait times the number of significant differences varied by the hour and by scenario. Across all scenarios, the initial and last hour were usually the same between systems as there are very few patients during those hours, and the change in arrival rate has a lesser effect on those hours than on the peak demand hours. The peak demand hours also had a large number of overlapping confidence intervals from Hour 5 to Hour 9. This is primarily in the average and lower scenarios however, as the difference between systems grows sharply in those hours as shown in Figure 29, with the decentralized patient wait time increasing steeply. Overall around 40 to 50 percent of hourly times were not significantly different for the average and reduced scenarios, while for the higher arrival rate scenarios the rate is between 18 and 22 percent.

Overall, this shows that despite the additional step the patient wait time is better for the centralized clinic, especially if the additional receptionist is added to the central admission location. As a system, a centralized approach works better for the increased rate tables given that the central admission location is adequately staffed. The central admission location is the key weak point for the centralized system, but while all clinics suffered in the decentralized approach for the increased rates, if the CAL is suitably staffed then the stress per clinic is far reduced in the centralized system as the Check-In process is far faster. In conclusion, while the maximum times may be worse for the centralized system in some scenarios, if the central admission location staff is adequate then both the average clinic wait time and patient wait time will be less than a decentralized clinic with a higher rate.

5.3 Disparity in Clinical Mixture Experiment

Organization A has generally equal amounts of patients who go to each clinic though the mixture changes per hour. By increasing some clinics to have a larger percentage of the total mixture we can see how each system fairs in clinical organizations where one or a few clinics have the majority of patients with other clinics nearby. Organization A's 16 clinics have very different levels of patients per day on average as well as the hours of their arrival as shown in Figure 30. The differences between clinics being considered to be centralized change from organization to organization. Some organizations may have multiple clinics that have no large disparity in arrivals while others may have one or a few clinics that are far more visited than the other clinics for a myriad of reasons.

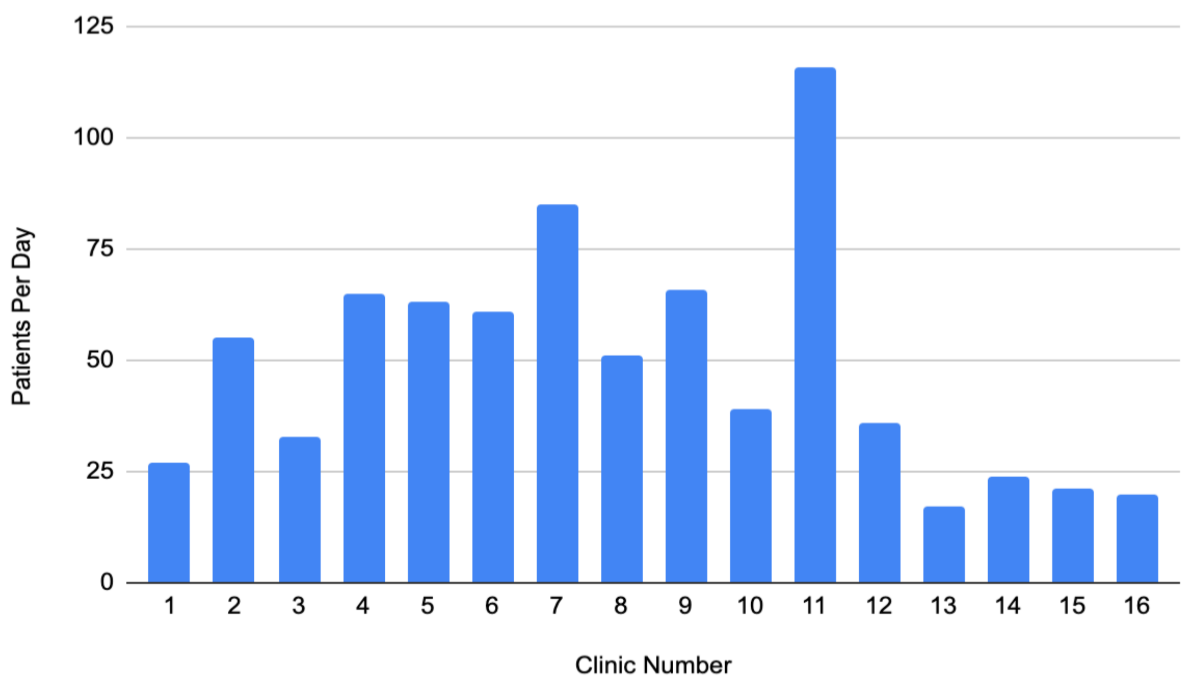

Figure 30: Patients Per Day for Each Clinic

To account for other organizations with different distributions than Organization A, four different scenarios were chosen. The first of which was an equal distribution across all 16 clinics. Due to the variation of the model, this does not mean that every clinic will receive the same number of patients per day. The number of patients who arrive on average each hour has not changed, only the distribution for which clinic they go to. For example, while in the current state of Organization A there are 7.95 patients who on average arrive between 6 AM and 7 AM, though some clinics are closed then and have a zero percent chance of having one of those 7.95 patients going to that clinic during that hour. In the equal distribution clinical mix, those 7.95 patients have an equal chance of going to each clinic.

During a run, 7 or 8 patients will arrive, as only whole numbers of patients are allowed, and therefore not every clinic will have a patient assigned to them during that time as there aren't enough patients. The equal distribution approach was the first of the four scenarios seen in Figure 31 that was created, but the following three scenarios are for situations when 1, 2, or 3 clinics have a larger share of the distribution with one half, one third, or one quarter chances respectively. As the scenarios progress, the arrivals per day for the large clinic(s) will decrease as well as the number of patients at each smaller clinic. However, the initial phase does increase the number of patients not just for the large clinics, but many of the other clinics as well who previously only have 20 patients, and now have their capacity under more strain.

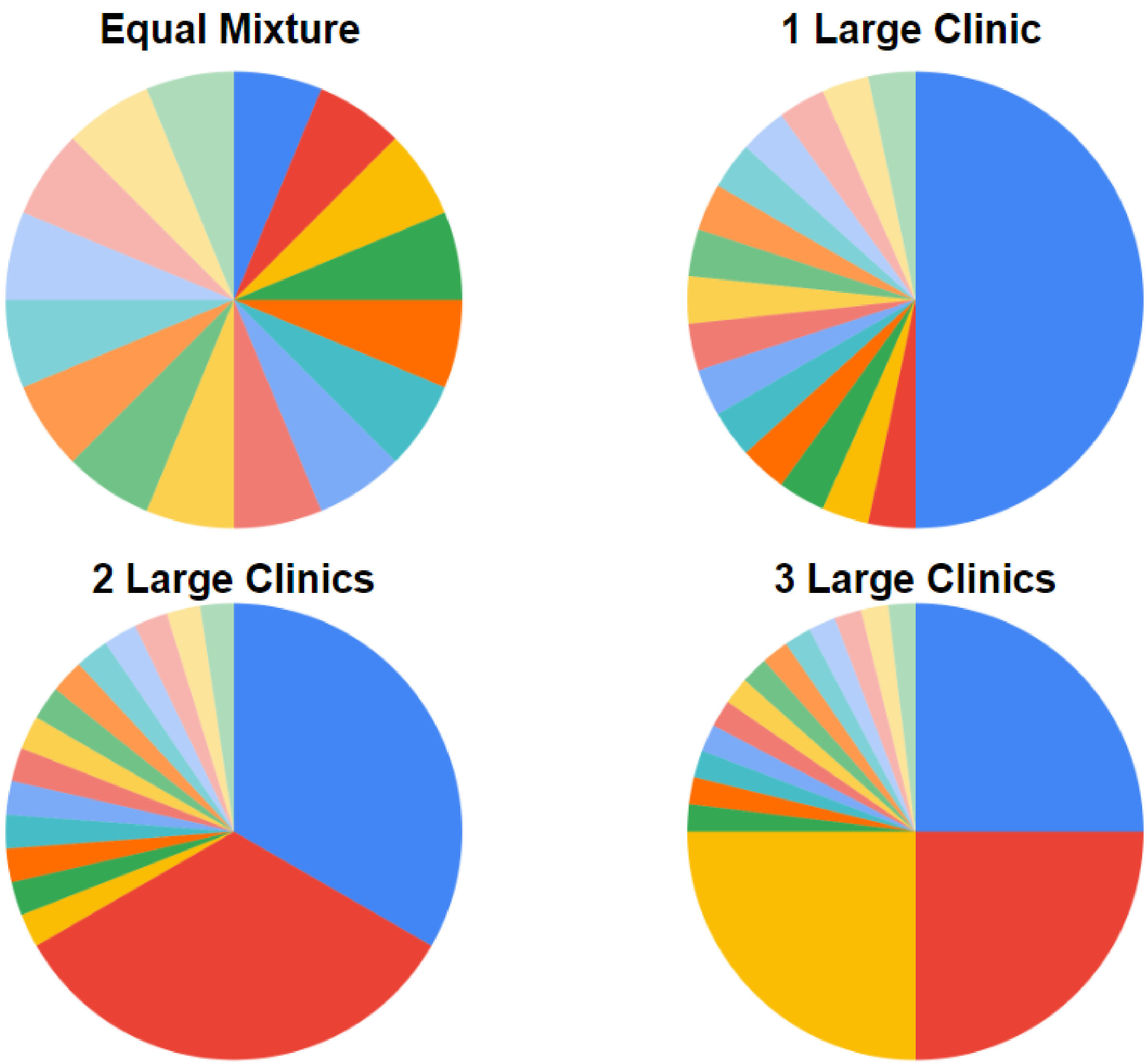

Figure 31: Clinical Mixture Scenarios

The four scenarios seen in Figure 31 are the same distribution for all 12 hours of the model run. While the current state arrival distributions vary by hour, estimating these changes would have been completely arbitrary for the clinical mixture scenarios. The centralized model was set to Staff Level 2 for the 300 runs while the decentralized model was set to the current staffing numbers.

The clinical mixture for multiple appointment patients was not changed although the clinical arrival mixture was. This allowed for more variation in the model and as only ten percent of patients have multiple appointments impacted the overall performance minimally.

Figure 32 shows the average clinical wait time across the clinics. As the staffing level was unchanged the decentralized system performs better in the third scenario as the staffing for Clinic 2 is 4 receptionists. Despite this causing Clinic 2 to have a smaller clinical wait time than it might otherwise have, overall the results show that the decentralized system is less suited for having particularly high-volume clinics. This is seen in the equal distribution scenario as well as each clinic should get roughly 49 patients per day which is a large increase for some clinics that only have 1 receptionist causing increased wait times at those clinics. The primary issue for the decentralized model was with the increased volume clinics, even though those clinics had at least 2 receptionists and at most 4 receptionists, the constant distribution made a steady stream that increased hourly patient wait times and queue times at Check-In and Check-Out. Staffing changes to both systems could be easily made to find a better fit for each that brings down the wait times, but the results show that the central admission location, when adequately staffed, can serve as a key buffer for high demand clinics while keeping the needed capacity of the less used clinics lower to make the entire system more operational for larger levels of disparity. While Figure 32 shows the average clinic wait times for each scenario, Figure A1 in the appendix shows the maximum time and Tables A10 and A11 show details about the decentralized and centralized runs.

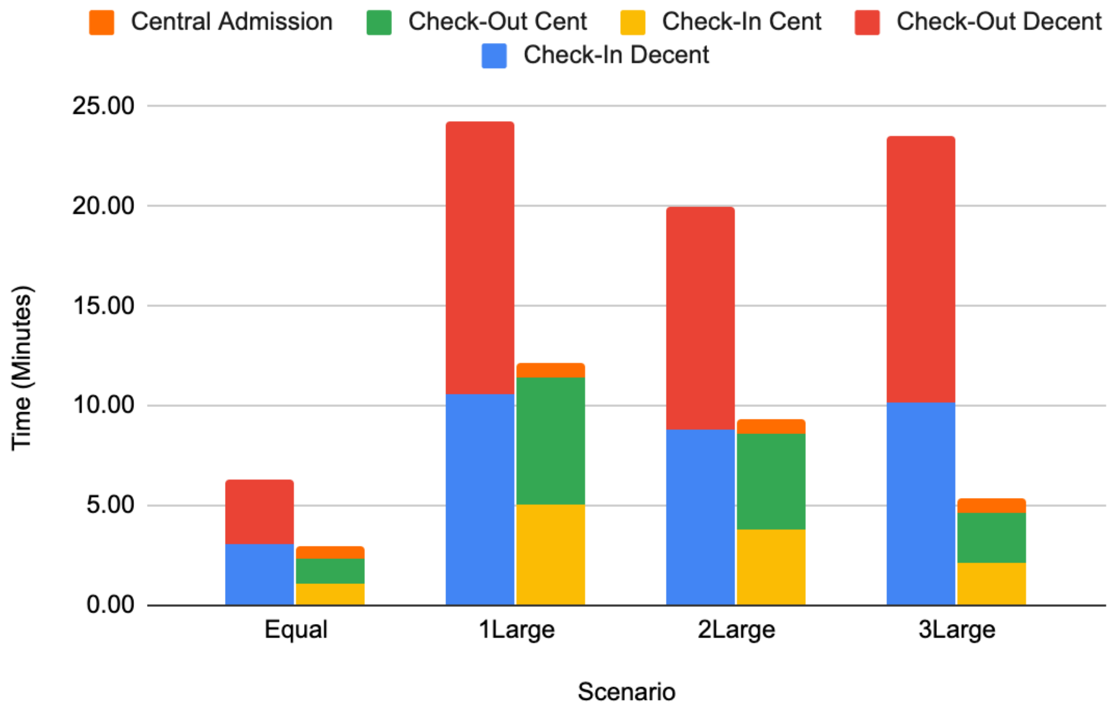

Figure 32: Clinic Wait Time Results of Mixture Disparity Scenarios

Table A12 and A13 in the appendix show that the average and maximum clinic wait times are significantly different and so the findings above are relevant when selecting a system based on the clinical mixture factor. In conclusion, while staffing could improve the results seen above the main takeaway is that with comparable staffing, the centralized system has a better buffer for higher demand clinics while easing pressure on lower demand clinics as well. This makes it suited for dealing with disparity between clinics as long as the central admission location is not the bottleneck in the process it can reduce the check-in process time for all clinics reducing the effect of the disparity in the clinical mixture.

5.4 Multiple Appointment Percentage Experiment

Organization A's current amount of multiple appointment patients is estimated to be around ten percent, but other organizations may have a greater or lesser amount of multiple appointment patients dependent on the level of interactions between clinics and their overlapping patients. The percentage range of 0 percent to 40 percent in intervals of ten percent was tested to see if one system over the other was definitively better for multiple appointment patients. As multiple appointment patients affect both clinical wait time and patient wait time, those were the two metrics of interest. The throughput metric was most likely to change from scenario to scenario within the system, as more patients would still be in the facilities at the end of the 12 hours, than from decentralized to centralized and so that metric was recorded but not the subject of an in-depth comparison between the systems.

The number of multiple appointment appointments depends on how interweaved the multiple clinics are or can be in the organization. Some clinics may have no interactions with others especially if the operations or processes performed there are incompatible with those at other clinics and require a medical resting period afterward. There could also be completely separate segments of society that each clinic is helping, for example, a pediatric clinic and a clinic for elderly patients will have no patients who have appointments at both. The 40 percent upper range of multiple appointment clinics is probably unlikely in the real-world, especially based off of Organization A's current state data, but these experiments can provide better insight for those organizations with differing rates of rerouting.

Once the experiments were completed the times for all 5 scenarios were compared against each other. As the percentage of multiple appointment patients increased, the number of patients still in the system increased as well. While every run had an average rate of 779 patients per day, the number of visits per clinic would rise along with the multiple appointment percentage as those patients would visit more than one clinic. Therefore, an increase in both clinical wait time and patient wait time is to be expected of both systems, regardless of how suited they are for multiple appointment patients.

The results show once again on average the wait time per clinic is better in the centralized model at the beginning and the difference in time only becomes wider as seen in Figure 33. While the centralized system does experience a growth in the average clinical wait times, the growth is minimized due to the central admission location. Patients only need to go through the central admission location once in the centralized model and then the handoff procedure at each clinic.

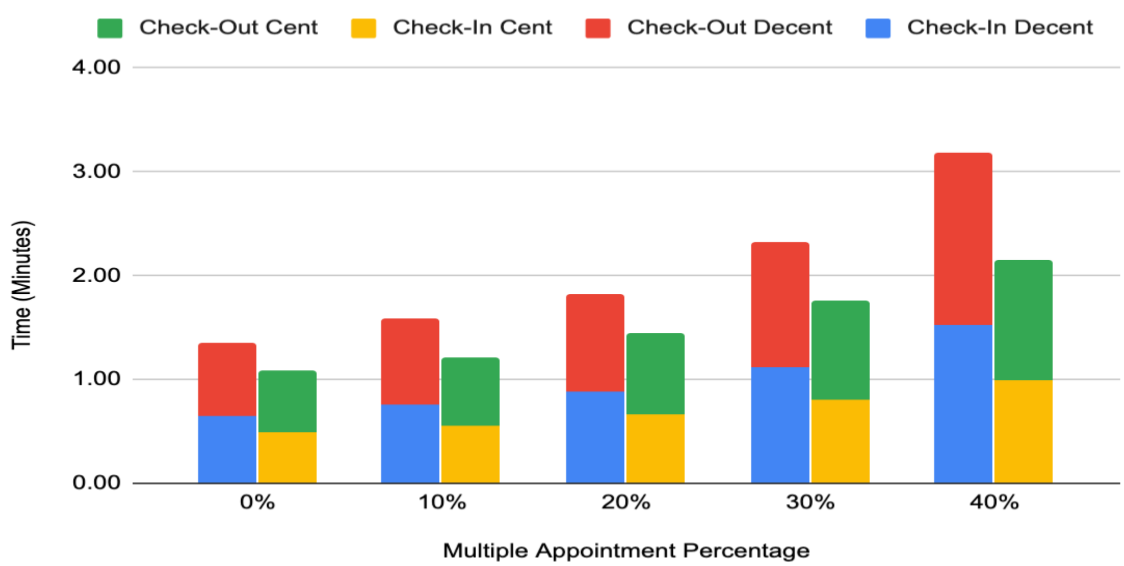

Figure 33: Average Patient Wait Time per Multiple Appointment Scenarios

However, while the average times for the centralized system are shorter than the decentralized system, the maximum clinical wait times are actually larger for the centralized clinic as shown in Figure 34, with the full details of the run seen in tables A14 and A15. It is important to note that while the maximum time was greater than the decentralized version, the average time was not which implies that the maximum clinic wait times are more representative of outliers. Whether or not the average or maximum clinic wait time in this scenario is more important is dependent on the healthcare organization and their priorities.

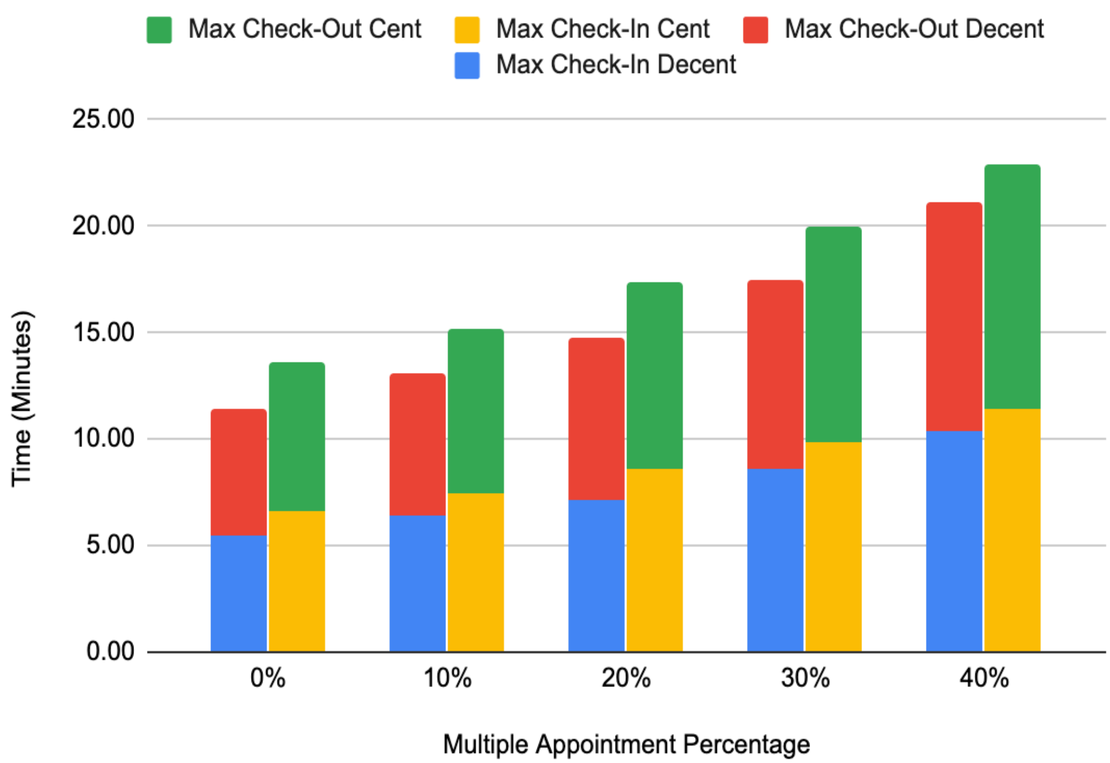

Figure 34: Maximum Patient Wait Time per Multiple Appointment Scenarios

Overall the times in Figure 33 and Figure 34 were significant as shown in tables A16 and A17 in the appendix. For the average clinical wait time, the only time when the difference was not significant was for the check-out wait times in the zero percent multiple percent scenario. While the check-out wait time in that scenario was relatively equal, the decrease in check-in wait time for that scenario and the decrease of both check-in and check-out wait times for the other scenarios show that overall the centralized system had a statistically lower average clinic wait time. For the maximum wait times, the decentralized clinic always had a statistically lower wait time until the 40% multiple appointment patient scenario. The overall trend of confidence intervals was an increase in the gap between scenarios for the average wait time as the percentage of multiple appointment patients increased, while for the maximum wait time the gap decreased over time as the percentage of multiple appointment patients increased.

Multiple appointment patients do cause each clinic to have more visitors and increase clinical wait time, but they also have to travel to multiple clinics and wait at each one which increases the average patient wait time. Figure 35 shows the zero percent and 40 percent multiple appointment patient chance scenarios in terms of the patient wait time per hour of their arrival. As seen in the top two graphs the patient wait times are similar for the two systems, with the decentralized system generally taking longer in the earlier hours of the day and the centralized system taking longer for patients later in the day. By scenario 5 the difference has grown as the decentralized model is almost always longer for patients. The confidence intervals show the first and last hours not being significantly different from hours 6 to 8 also having overlapping confidence intervals. This was primarily in the 20 percent and less likelihood of multiple patients, as the amount of statistically different hours increased along with the percentage of multiple appointment patients.

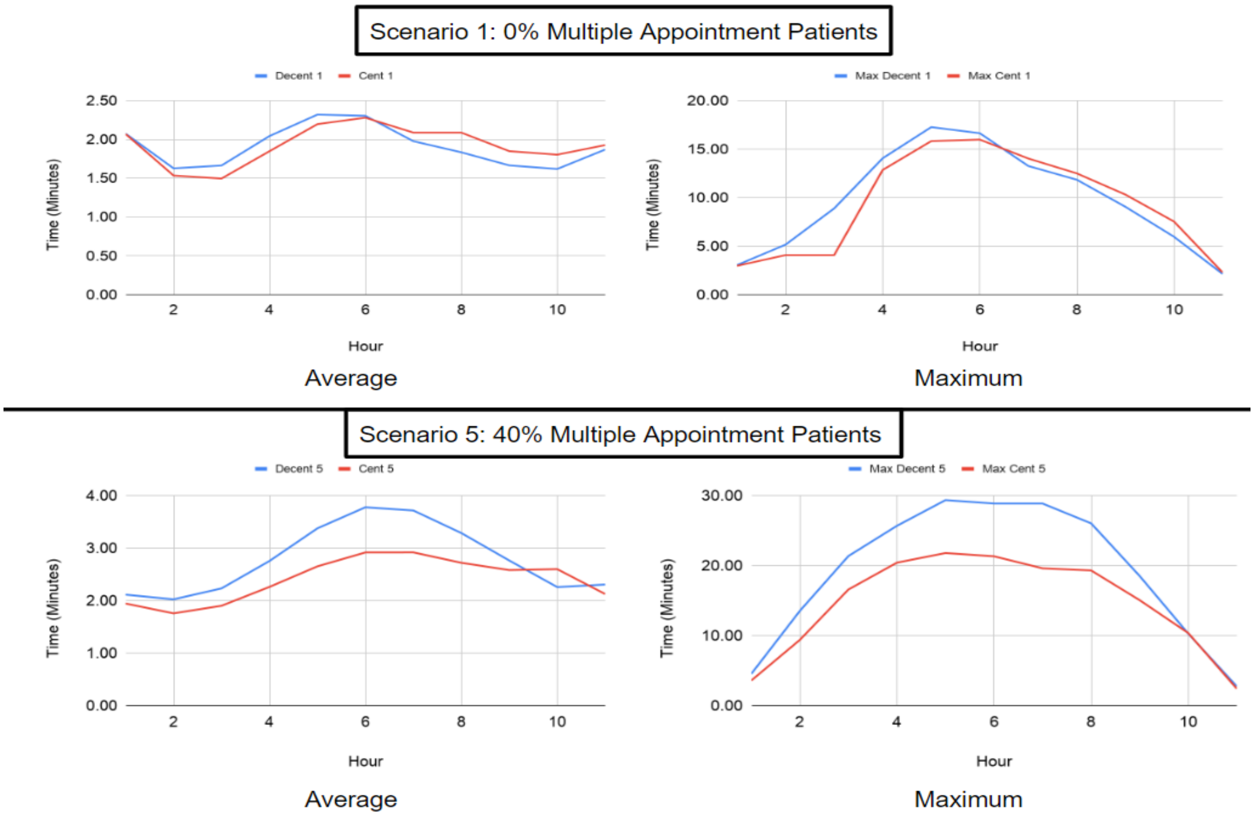

Figure 35: Scenario 1 and 5 of the Multiple Appointment Scenarios

In conclusion, when there is only a small percentage of multiple appointment patients, then other factors are more instrumental in choosing between the two systems as they have similar metrics. However, as the percentage of multiple appointment patients grows, the times for both clinical and patient wait times for the centralized system become shorter than the decentralized system, which shows the centralized system is clearly better for a higher number of multiple appointment patients.

5.5 Travel Time Experiment

Organization A has many clinics located closely together, but if traveling time is increased the patient's overall wait time increases as well. The current travel times were estimates, but increasing those ranges by a multiple of 2 and 3 can show system performances for organizations in which clinics are either located farther apart or have less-mobile patients or indirect pathways than Organization A has. As travel time is directly related to the patient wait time and not the clinic wait time, only the former was used as the deciding factor between the two systems.

The double and triple travel times are still under the assumption that the site in which the clinics are located has longer times associated with travel inside the site across the facilities. The increased travel time is not necessarily a reflection of facilities that are located far apart. If the location of the clinics is far apart that the act of visiting one would require driving the car from the main lobby and parking it again then the twice and triple scenarios will most likely not reflect that situation. In that situation, the decisions on whether to include travel time in the decentralized model would be the key deciding factor as shown in Figure 36. The average patient wait times increase the same amount for both the decentralized and centralized models and do not clearly indicate that one system is better than the other. The maximum patient wait time is seen in Figure A2 in the appendix along with the decentralized results in Table A18 and the centralized results in Table A19 in the appendix.

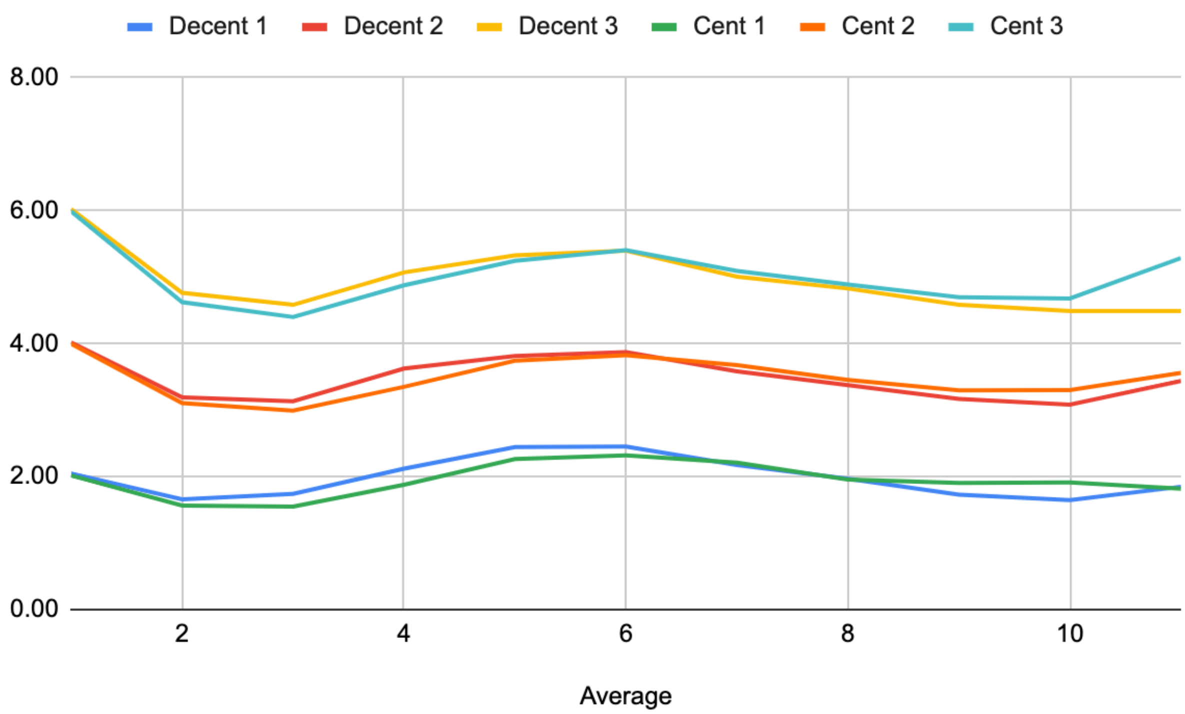

Figure 36: Average Patient Wait Time of Travel Time Scenarios

Figure 36 would seem to indicate that the average patient waiting time differences are minimal and Figure A2 would also imply that for the maximum waiting times. In Tables A20 and A21, only 50 to 60 percent of each scenario has significantly different wait times, though this percentage does not increase or decrease with the travel time, but rather fluctuates. Many of the other hours were close to insignificant differences. As 500 replications were run for each scenario the width of the confidence intervals were relatively small. As seen before with other runs, the primary hours where the results were statistically similar was the first hour, last hour, and the period from hour 6 to hour 9. However, while other times may be statistically different, in practice the amount of variation in travel time is most likely greater in reality and therefore the confidence intervals are most likely wider with more frequent overlaps.

The double and triple travel times are still under the assumption that the site in which the clinics are located has longer times associated with travel inside the site across the facilities. The increased travel time scenarios may not be representative of an organization with clinics in separate facilities considering centralization. In that scenario, the deciding factor is whether or not to use the initial travel time to the first appointment clinic in the decentralized model. As Organization A's current state involves patients entering through the lobby in the main hospital, the travel time was considered a part of the total patient wait time. However, if the clinics being modeled are far apart that there is no central starting point for the patients, then it falls to the organization on whether or not they consider that time to be a part of the patient wait time. Removing that initial travel time would remove times between a quarter of a minute to 5.25 minutes from the decentralized model in the average travel time scenario, and would thus have a large impact on the total wait time. Also, in a decentralized system, the initial travel time to the first clinic would be considered to be an accepted time by the patients similar to the time it takes for patients to get to the lobby of the main hospital in the current state decentralized model. The organization might still record the travel time for multiple appointment patients in that scenario, so the average patient time will still be high due to travel.

In conclusion, if all clinics are located in the same facility in walking distance, or using the assistance of escalators and/or elevators, then increased travel times do not indicate a clear winner.

However, if the clinics are located farther apart than Organization A and there is no central starting point like the main hospital lobby is in the current state, then the initial travel time can be removed from the patient wait time if the organization decides to do so. The centralized system cannot have this time removed as all patients must go to the central admission location which acts in a similar role to the central starting point in the decentralized model. This would most likely make decentralized systems better suited for more distant clinics, though in this case the scope of the number of clinics being centralized can be changed to better fit an approach.

5.6 Number of Clinics Experiment

The literature read shows that Organization A is on the larger end of the spectrum for the number of clinics located in close facilities. By altering the number of clinics from 4 clinics on the lower end and 20 on the higher end we can see the effect of the number of clinics on the success of each system. Separate intervals of 4, 8, 12, 16, and 20 clinics were tested across 300 replications using existing mixtures and staffing for the clinics. For the 20 clinics, the four clinics were randomly added on floors that currently had only 1 other clinic.

The four clinics were given the average mixture for both hourly distribution and rerouting opportunities. As shown in Figure 30, every clinic has its own average number of patients each day. The total of all 16 clinics is equal to 779 patients which was used as the basis for the multiple arrival rate scenarios. However, in the reduced clinic number scenarios where there are only 4,8, or 12 clinics, the average changes as well. Since each clinic’s average was already known this was used in each scenario to calculate a new total admission each day as well as separate arrival rates and hourly distributions. This was done as keeping the original rates would not be representative of the demands of the clinics. The 4-clinic scenario is under the assumption that all 16 clinics exist but only 4 of the clinics are in scope, so the total average admission is the sum of the patients who visit Clinic 1, 2, 3, and 4 each day. The percentages for hourly distribution were then recalculated to make sure the distribution of the hourly arrival was more accurate to the 5 scenarios. The arrival rate tables for each scenario is seen in Table 8 below.

Table 8: Arrival Rates for each Clinic Number Scenario

Hour	4 Clinics	8 Clinics	12 Clinics	16 Clinics	20 Clinics
1	1.81	1.83	7.77	7.95	10.60
2	12.36	23.98	42.59	47.61	63.39
3	25.79	65.09	100.07	112.62	139.41
4	30.53	74.47	115.61	131.86	164.60
5	27.56	69.87	109.60	123.47	155.55
6	21.52	48.02	78.71	87.99	111.60
7	19.93	48.36	78.37	84.8	106.90
8	21.14	53.64	80.21	90.31	110.51
9	13.65	37.56	55.82	61.69	74.69
10	5.34	15.79	24.33	26.64	32.50
11	0.30	1.30	3.59	3.73	4.82
12	0.07	0.12	0.40	0.4	0.51

The current state of Organization A has 16 clinics and so creating the reduced number clinics was easy to do. Their averages remained unchanged but the excluded clinics had their average patients per day along with their percentage per hour removed. For the 20-clinic scenario, those new clinics were given an average number of around 41 patients per day and were given randomly selected hourly distributions from other clinics. This allowed those clinics to be realistic as there is no information on an additional 4 clinics that could have been included in the scope. The modeling effort also included selecting random locations for the four additional clinics in floors that only had 1 clinic in the current state. After being placed randomly the process for adding the pathways and times to the clinics followed the methodology section for adding new clinics in the Simio model. Staffing for the models was estimated at first based on staffing performances on clinics with similar demands. Staffing was altered as needed be in case of any unexpected bottlenecks with the new clinics. The clinical mixtures used in each experiment are seen in Table A22 in the appendix. To compare the two systems both the clinical wait time and patient wait time were compared.

The results of the experiments show a clear indication that a decentralized system performs better for the fewer clinics while the centralized system works better for organizations with more numerous clinics being centralized. The first indication of this is in the clinical wait time seen in Figure 37. The increase in clinics does not cause a perfectly linear increase as each clinic remained its current state average (for the 16 clinics that are in scope) and the addition of Clinic 11, which has the highest number of arrivals per day caused the 12 clinics model to shift in a more unexpected manner. Figure A3 in the appendix shows the maximum clinical wait time which experiences a somewhat similar fluctuation in results. For both average and maximum wait times, the centralized system is clearly more time consuming than the decentralized model for fewer clinics. The reduced staffing in the centralized system was still volatile to influxes of patients and while the maximum clinic times are usually higher in the centralized system they were a more significant section of the results than the usual outlier long wait times. The maximum clinic wait time remained higher for the centralized system until the 20 clinics scenario when the times became equal, while the average wait time was nearly equal around the 12 clinics scenario and less than the decentralized time in both the 16 clinic and 20 clinic scenarios.

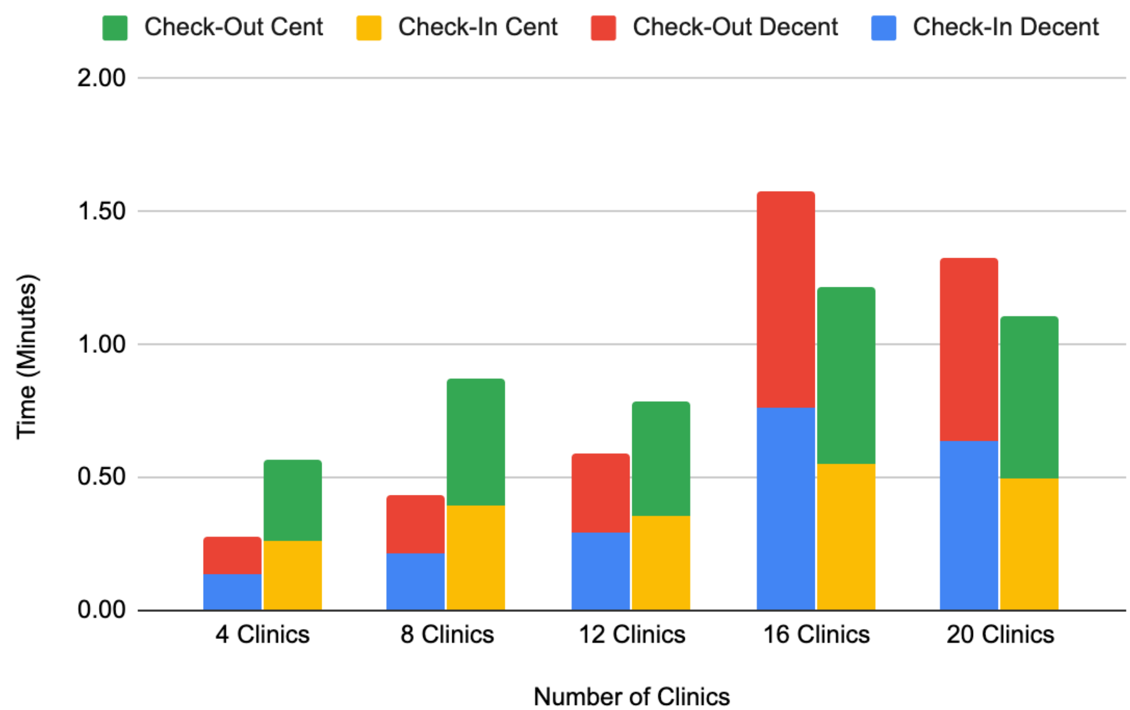

Figure 37: Average Clinic Wait Time per Clinic Number Scenario

The confidence intervals in Figures A25 and A26 show that most clinical times are statistically different with the exception of the average check-in time for 12 clinics and the maximum check-out wait time in the 20-clinic scenario. The patient wait time shows a similar result due to the increasing number of clinics. For both the 4 clinic and 8 clinic scenarios, the decentralized model performed better than its centralized counterpart as shown in Figure 38. The large peaks around from hour 4 to hour 8, roughly an hour after the beginning of the morning peak in demand, show the maximum patient wait time increasing and taking a great toll.

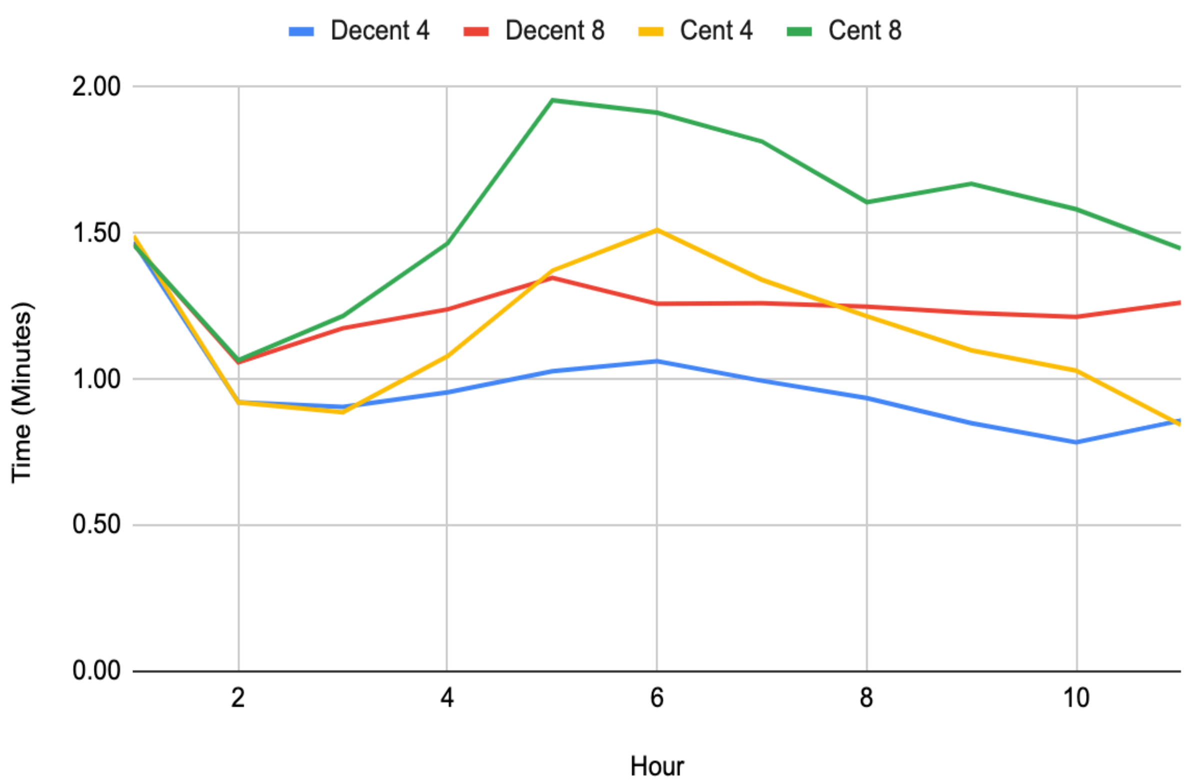

Figure 38: Average Patient Wait Time per Hour for Lower Two Clinic Number Scenarios

The average wait times for the two highest scenarios in Figure 39 show a near equal patient wait time between scenarios. The centralized system usually performs better at the beginning of the day but experiences a longer gradual drop compared to the decentralized system. It is also relevant to note that in the final 20 clinics scenario, the 4 additional clinics were staffed by 3 receptionists each in the decentralized version and only 2 receptionists in the centralized version (though the central admission location gained another receptionist). This caused the overall difference in staffing to be 13 receptionists. So, while the times may be similar, the amount of staffing needed for these times is different. All results from the decentralized and centralized experiments are in Table A23 and A24 in the appendix.

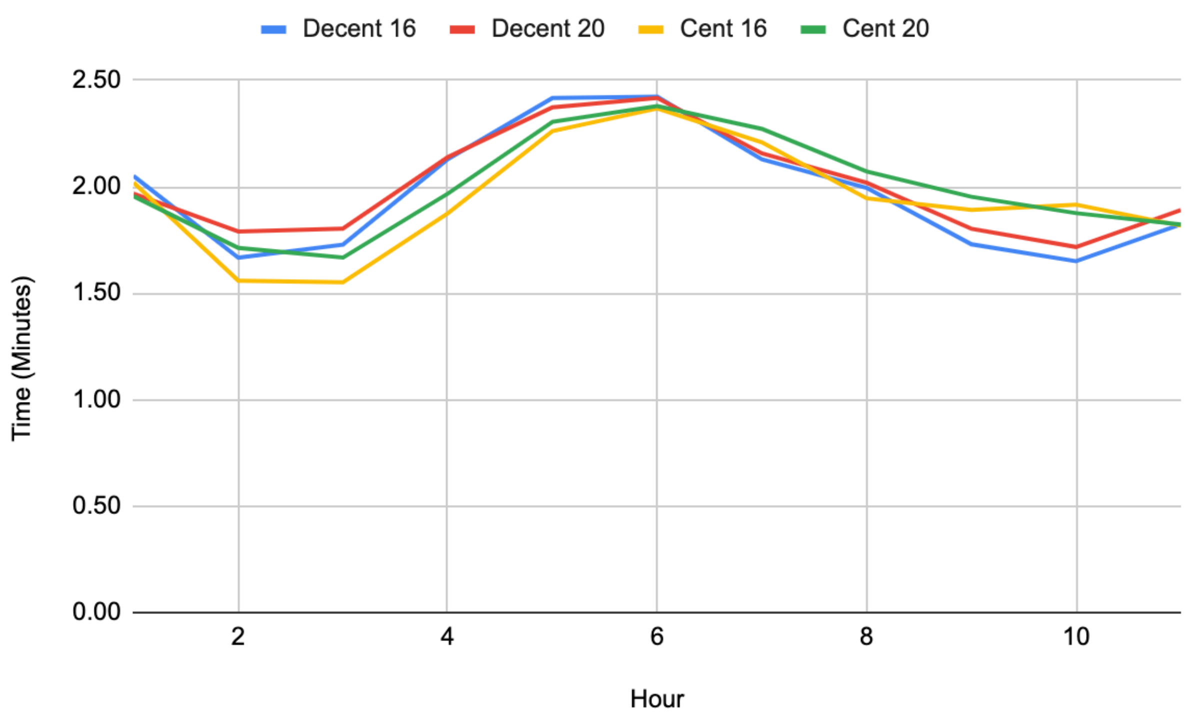

Figure 39: Average Patient Wait Time per Hour for Upper Two Clinic Number Scenarios

In conclusion, the decentralized system appears to be the clear winner for fewer clinics as the maximum clinical and patient wait times for the centralized system have a more pronounced impact on the centralized system's average clinic wait time and patient wait time. The centralized system performs best for a large number of clinics overall, as the shorter process times allow for most patients to have short wait times. However, the vulnerability of the centralized system is that the reduced staffing can be overwhelmed by large amounts of frequent demand, and maintaining the proper number of receptionists at the central admission location. In a site with more clinics this vulnerability becomes less pronounced, and an equal or lesser clinical wait time and patient wait time can be achieved by a significantly smaller staffing level.

6 Validation Case Study

The large healthcare organization, hereafter referred to as Organization A, has a large number of clinics spread over two buildings in a single site in a metropolitan area. Initial work was done to refine the scope of the decentralized and centralized models. Multiple clinics were considered but were decided to fall out of scope due to regulatory restrictions or due to not being considered by Organization A to be able to be centralized. Finally, a total of 16 clinics across 2 closely conjoined buildings were decided to be the ones modeled. For the sake of anonymity, these clinics are referred to by number and there were no medical or operational restrictions that would stop patients from visiting one clinic because of their visit to another one the same day. Therefore, the patient flow included connections from each clinic to every other clinic spread across the 2 buildings.

6.1 Validation Model Inputs

The clinics were also not located on the same floor, with one building having 7 floors in scope while the other has 5 floors. Relating to the mobility issue previously mentioned, these larger than average facilities meant that travel times were not only significant for multiple appointment patients but also single appointment patients as well. The structure of the two facilities is seen below in Figure 40.

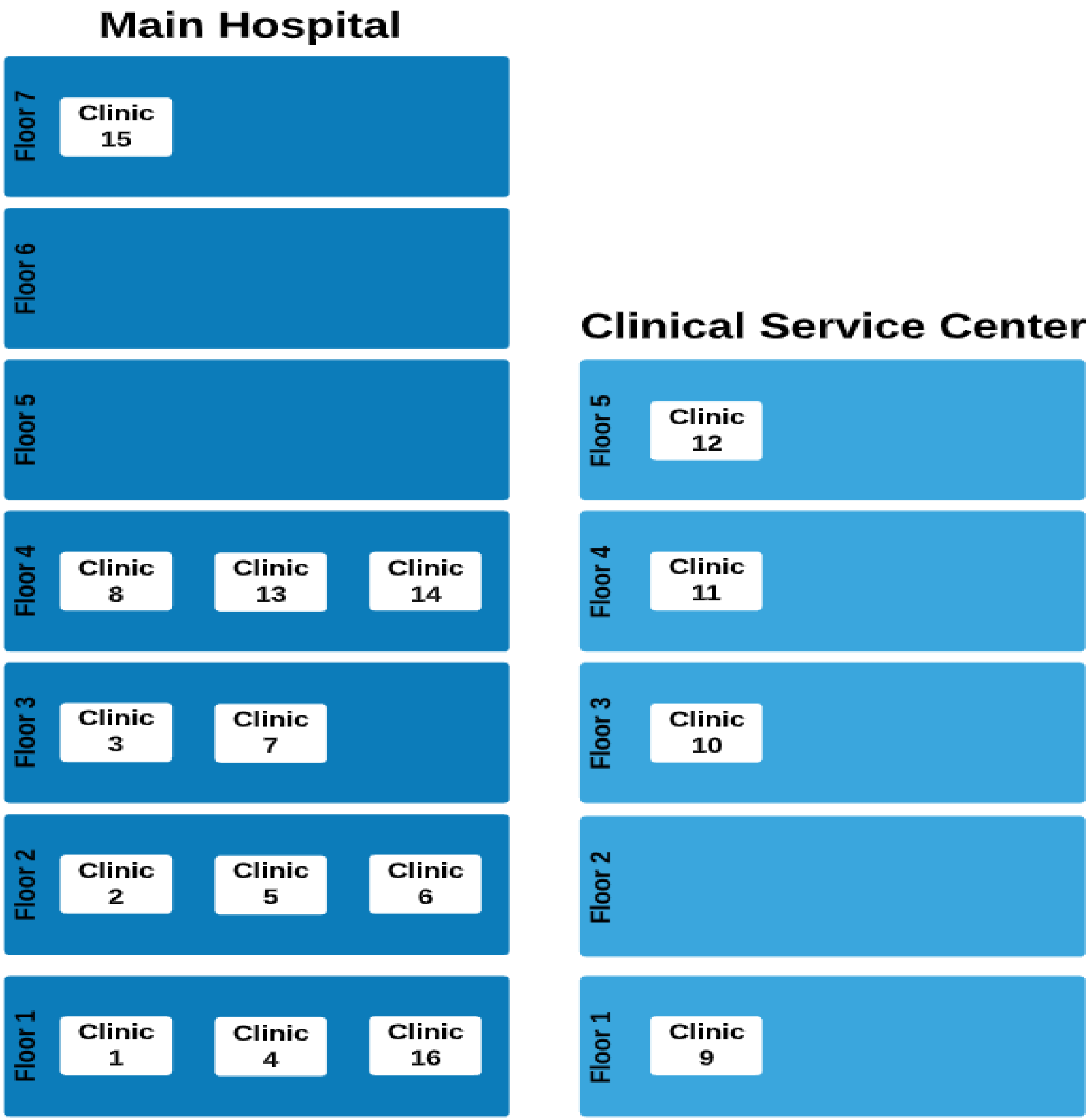

Figure 40: Clinic Positions in the Two Facilities

Patients could enter on the first floor of either building, though in the current state most patients enter through the main hospital lobby. Originally, the dimensions of the floors and the clinics were planned on being somewhat incorporated into the models, though with a focus on interior clinic dimensions and general assumptions for the rest of the floors. However, due to the Covid-19 pandemic, it became impossible to go to the clinics and map out those general dimensions, and so a more abstract version of the two buildings was settled upon. The inability to access the facilities made determining travel time more difficult to do, and so a new assumption was made for travel time shown in Figure 41. The times below are in minutes with an assumption that if someone is traveling to another location in the same building on the same floor, then it will take between one to three-quarters of a minute to travel, depending on mobility and the ability of resources such as elevators. If the patient needs to travel up or down a floor, the minimum time is increased by a quarter of a minute while the maximum time is increased by three-quarters of a minute. Traveling across buildings also increases the time by 15 seconds on each end of the distribution.

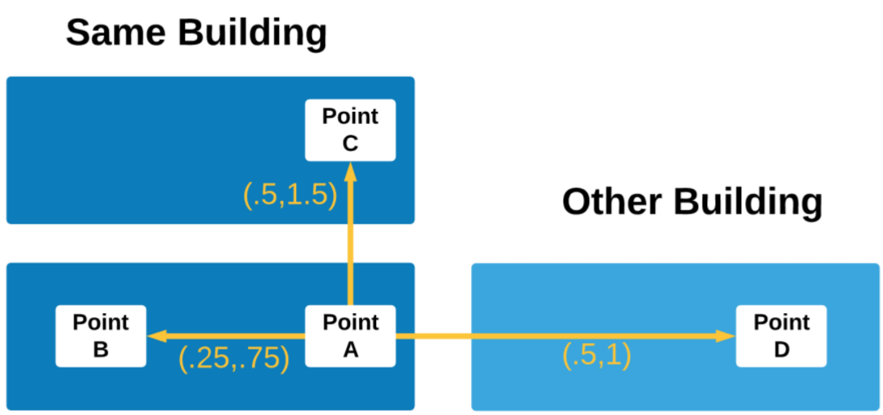

Figure 41: Travel Time Estimation Tool

Each patient has an equal chance of picking a time from the range given, for example, a patient traveling from point A to point B in Figure 41 has an equal chance of it taking .25 minutes or .75 minutes or any time in between. These times compound on each other, a person traveling two floors would have the same increase of .25 minutes on the lower end and .75 minutes on the higher end for each floor, totaling in the minimum increasing by half a minute and the maximum increasing by a minute and a half. And if the patient were to cross buildings during that traveling an extra quarter of a minute would be added to their ranges. As the facilities are very large and interconnected, these travel time assumptions play a crucial role in the models.

Following the guidelines of the concepts illustrated in Figure 8, the secondary concepts for Organization A were chosen to be utilized in the decentralized and centralized model. These concepts can be seen in the figure below. Organization A needed most of the secondary concepts available and in fact, could have selected the remaining three as well. Multiple patient types and unique patient type processes were almost chosen for two different groups of patients, new patients and those that had to go to phlebotomy to get their blood drawn. This would have required the creation of additional processes for both registration and phlebotomy in the models and gathering the data for those processes, but these two groups were not made into separate patient types. The reason they were not selected was these additional processes were considered irrelevant to the latter steps and these patient types did not have different check-in and check-out procedures so their incorporation would have been irrelevant.

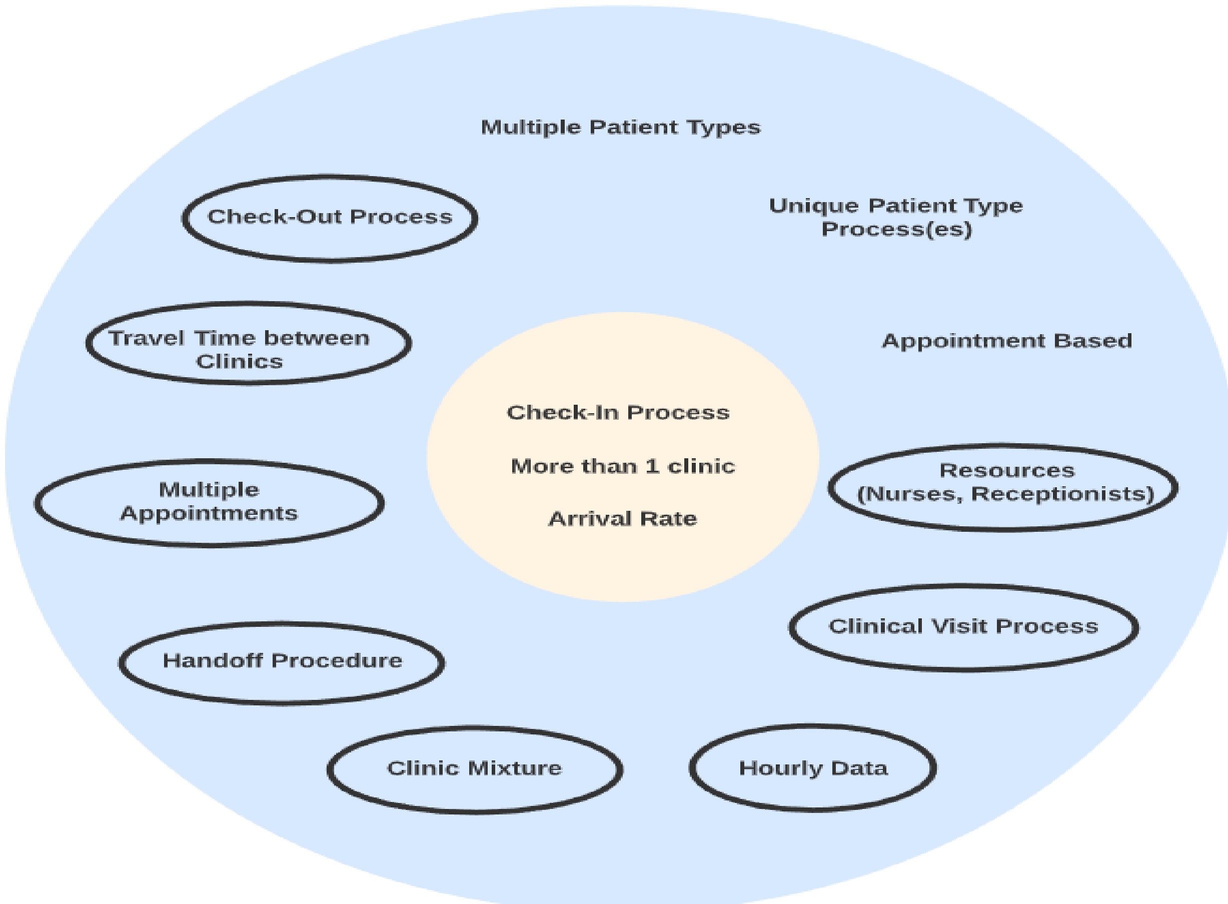

Figure 42: Secondary Concepts relevant to Organization A

While some clinics are appointment based, the appointment policy is not standardized with the process changing from clinic to clinic and receptionist to receptionist. Some patients may have a scheduled appointment 20 minutes before their examination and some may have more or less. After consultation with Organization A, it was decided to leave the percentage of appointments on time metric out of scope due to this and Organization A’s focus on other metrics. One of Organization A’s focuses was on staffing capacity as shown with the resources secondary concept. Organization A wished to see the effect of centralization on staffing capacity compared to the current decentralized state. The resource modeled for each clinic are the receptionists who perform the check-in and check-out processes. As the check-out process is modeled the visit time had to be modeled as well. The level of detail for this visitation process was left open-ended as the visit process time varied internally for clinics and between the clinics which each have their own specialization focus which requires different processes and times. Due to this, a flat range was decided upon, which will be explained in more detail later.

The arrival rate varied per hour and clinics would face peak patient arrival hours as well as some hours with no demand. The hourly spikes could result in capacity issues for some clinics if they do not have the necessary resources. Organization A already has a handoff procedure chosen and the separation point of the check-in process between the central admission location and the destination clinics are covered in more detail later. The standardization of both the check-in and check-out processes made the system easier to model and comparisons between centralized and decentralized and between clinics fairer and more accurate. The handoff procedure also plays an important role in multiple appointment patients who currently must go through check-in at each clinic. Organization A is very interested in seeing the effect of centralization for these patients, as mentioned earlier, multiple appointment patients would not want to have to deal with very long wait times. In a centralized model, the multiple appointment patient would have to go through one central admission process and the handoff procedure at each clinic that they visit during that day. A full 12-hour day was modeled for both the decentralized and centralized clinics though as some clinics are open earlier or close earlier than other clinics and therefore have no patients entering during certain hours.

6.2 Validation Admission Style

The decentralized model served as a good testing opportunity for the secondary concepts for Organization A. As the decentralized system was the basepoint for the two systems, is the current state, and shares plenty of similarities with the centralized system, it was created first. As it was impossible to visit the facilities of Organization A due to Covid-19, the model itself is an abstracted view of the facilities. The size of all floors is the same and the locations of the clinics in the model inside the floor have no relation to their actual physical location. The real-world distances are captured using travel times which will be discussed in more detail later. As the model is more abstracted than originally planned, the patient flow is somewhat more difficult to visualize than the ideal original version.

The current state of Organization A's clinics in reality is a decentralized structure. Therefore, the model represents the same patient flow, with fewer decisions to be made compared to the centralized model. As mentioned before the phlebotomy and registration locations were excluded from the scope of the model, and so the model outside of the patient entrance and exit only include the 16 clinics being modeled. As the decentralized state was the current state of Organization A this allowed for the results of the runs to be validated by a member of Organization A,

6.3 Validation Model

The patient entrance is located in the lobby of the main hospital in the decentralized model. The rate of arrivals is variable, with peaks occurring during the earlier 12 hours as shown in Figure 43. While the exact number of patients who will visit in a certain day changes based on the day of the week and many other factors, the distribution by hour is assumed to be the same for all days.

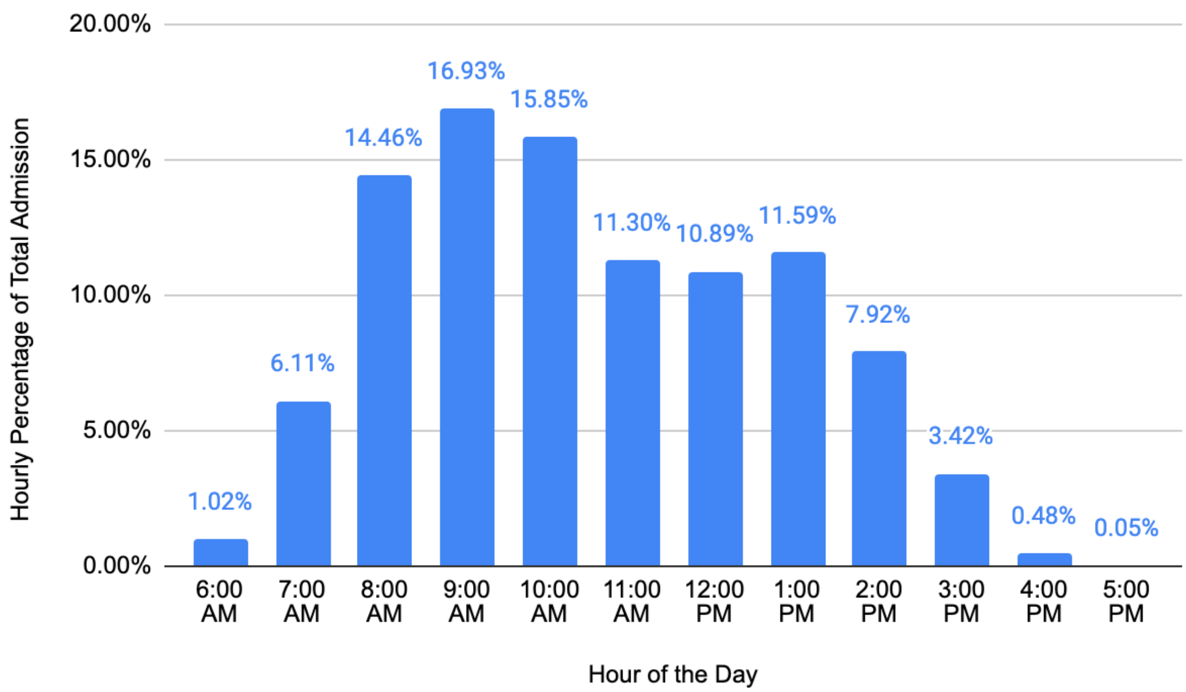

Figure 43: Hourly Distribution

Figure 43 shows each hour's percentage of the total admission for that day. These percentages were received from Organization A and show a clear peak from 8 AM to 10 AM along with a slight peak around 1 PM. Not all clinics are open for all 12 hours and so the percent of total admission for the first hour and last two hours. By using percentages, different numbers of arrivals per day can be implemented by multiplying the total by the percentage for each hour. For example, if there were a thousand patients who had appointments, at 8 AM the percent of the total day's admission is around fifteen percent and so there would roughly be 150 patients who arrive at that hour. Those patients all arrive in the main hospital and then head to their destination clinic. The probability of which clinic the patient will go to is heavily dependent on the hour of the day as shown in Figure 16 below.

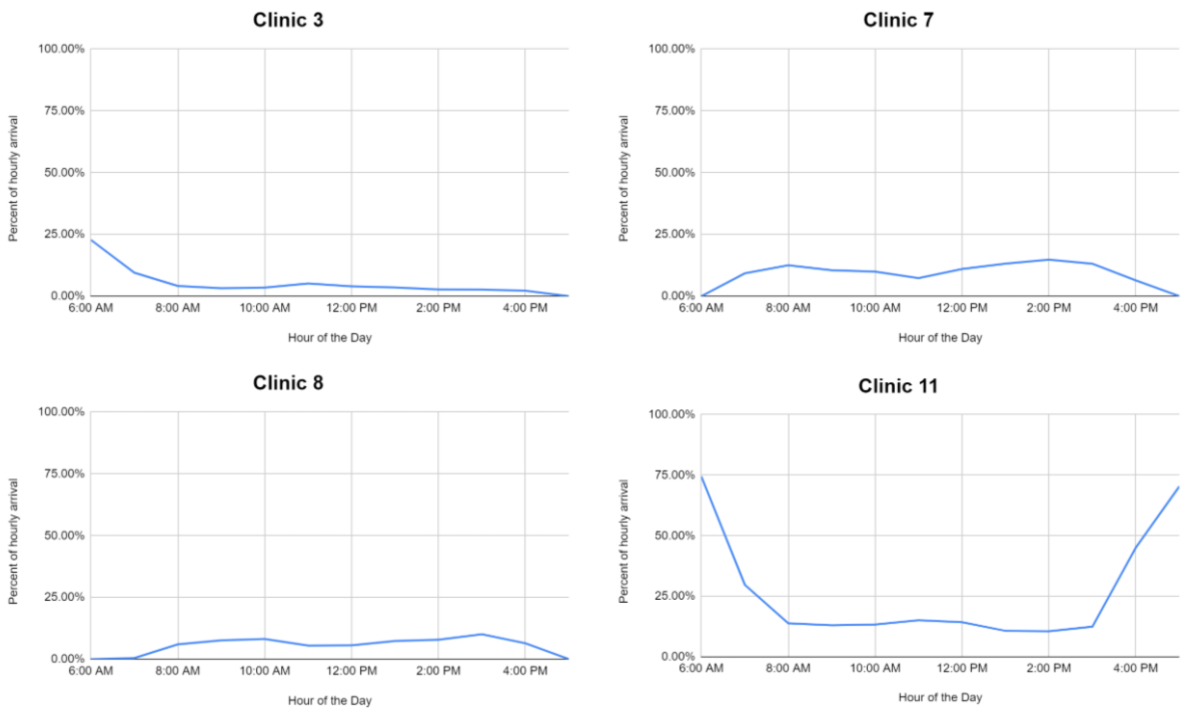

Figure 44: Example of Clinical Percentage of Each Hour's Arrival

Figure 44 shows the percentage for a few clinics of each hour's arrival, for example at 6 AM clinic 11 has the largest single percentage of that hour's arrival with nearly 75%. As some clinics are open later than others, there are certain hours where clinics have 0% of that hour's total arrival as seen with clinic 7 at 6 AM. While this may seem like a large number of patients, remember that from Figure 15 that the number of patients who arrive at 6 AM is 1% of the total day's admission. In the case where there are only 100 patients who arrive on a day from 6 AM to 7 AM, this would mean that the patient has a roughly 75% chance of going to Clinic 11, around a 23% chance of going to Clinic 3 and the remaining percentage is spread across other clinics. As there is only the singular patient, they would most likely go to clinic 11 and the other clinics would have no patients during this hour even though they have a percent likelihood above zero percent. These percentages are based on the average number of patients who arrive at each clinic over an hourly distribution for each clinic and the variation in likelihoods means that different clinics serve different amounts of patients per day.

Some of the smaller clinics in Organization A usually only have twenty to thirty patients in a single day, while others are in the upper sixty to eighty range on an average day. To determine the percent likelihood for the clinics, the average number of patients for each clinic for each hour was divided by the total number of patients per hour which is seen in Figure 45. That equation gives the percent for each hour shown in Table A1 in the appendix, which is read column by column. When a patient arrives at 7:12 AM the second column is used to determine the likelihood of which clinic that patient is heading to. The patient has the highest likelihood of going to Clinic 11 that hour as Clinic 11 has around a 30% likelihood of being chosen then, which generally decreases hour by hour.

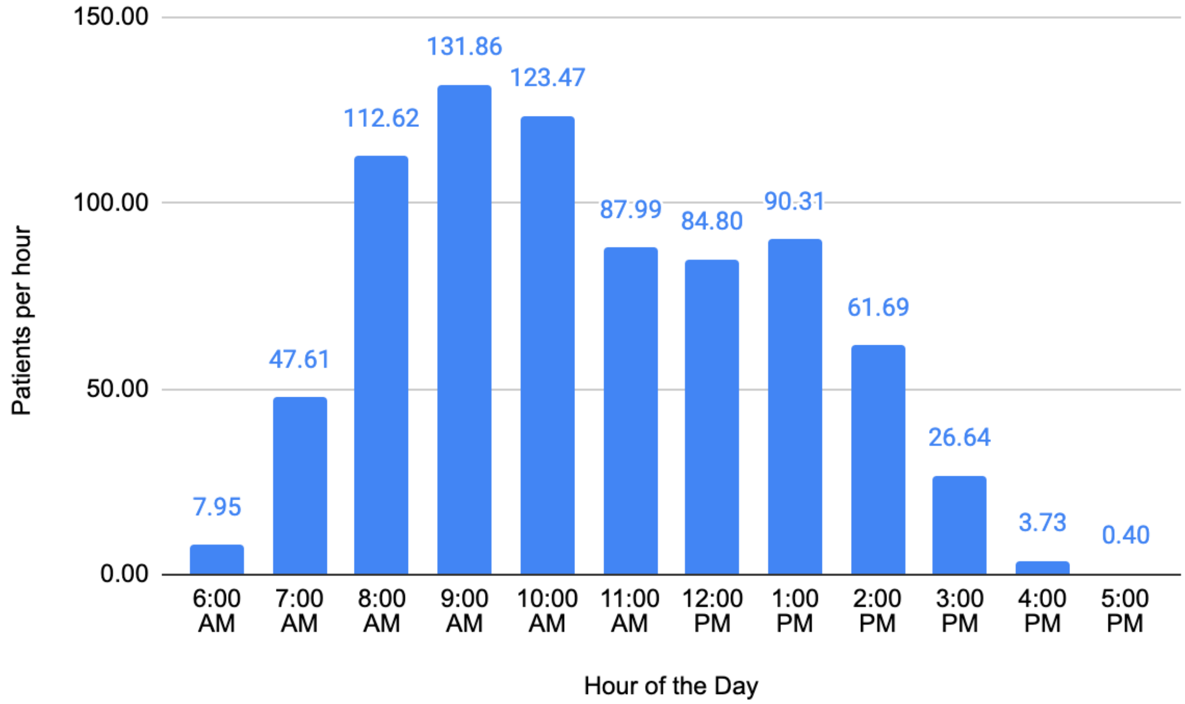

Figure 45: Average Patient Arrival per hour

Figure 45 shows the total number of patients for each hour who arrive at the facilities Organization A operates. On average there are 779 patients who visit the 16 clinics each day and so based on the percentages in Figure 43, Figure 45 was created. However, different total admissions can be used to create similar graphs to Figure 45. While we know the average volume of patients, there are certainly days that are above the average and days below due to weather, flu seasons, and many other factors. As the clinical percentages are based on the hourly arrival rates and the hourly arrival rates are based on the total admission, changing this number can increase or decrease the rate of arrival, affecting the number of patients who are assigned to each clinic. The distributions for both hourly arrival and clinic likelihood remain the same, but changing the number of arrivals has large implications for the capacity of the clinics. All patients independent of their destination clinic follow the same patient flow in Figure 46.

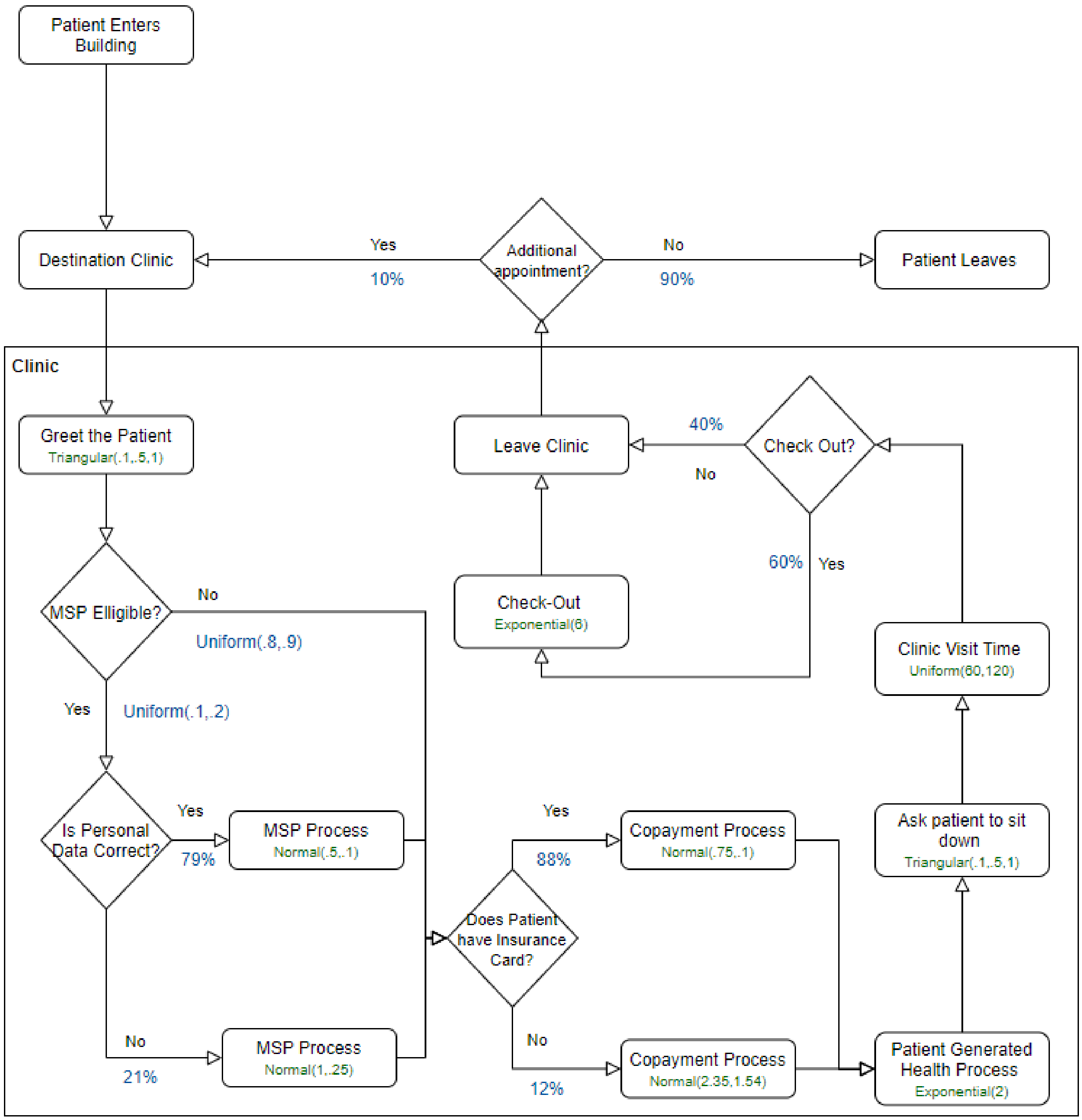

Figure 46: Patient Flow for Decentralized Model

The patient once entering the main hospital lobby then travels the path designated by their clinic assignment to their clinic's location (shown in Figure 40) and has a travel time from a range dependent on the clinic's distance from the lobby (Figure 41). Once at the clinic the patient will begin the check-in process if a receptionist is available by being greeted by the receptionist. Due to the Covid-19 pandemic, these processes were never officially timed as access to the facility became impossible and the processes shifted to a more remote structure different from the usual current state. Times for these steps were gathered from similar times found in other papers (Chand, 2009) and also from estimates based on a visit to the facilities, which while more preoccupied with the scope of the model and metrics also included some observations of the check-in process. These combinations of estimates were then vetted to more accurately match Organization A but are still estimates.

Somewhat more significant than the time estimates are the decisions in the check-in process. After being greeted, around 80 to 90 percent of patients skip the Medicare Second Payer (MSP) process, and so a uniform value is given to skip a somewhat significant section of the process. If the patient does go through the MSP process (generally if they are older patients) there is another decision for whether the personal data on Organization A's computer system is correct or if there are any inaccuracies or changes from the last visitation. While most patients will skip this step and a large percentage of those who do go through the process will take the reduced time. The next step of the process is to collect the patient's insurance information which is easier and quicker to perform if the patient has their insurance card or number on them or known. As many new patients get this card during registration and many patients historically have this card or information readily available around 88% of all patients take a shorter time to give their insurance information. For those who do not have their card or information the process generally takes longer with a much greater degree of variability. All patients must then perform the patient generated health process which is more focused on the reason for their visit and other information relevant to their reason to visit the clinic, which has an exponential distribution. Finally, the check-in process is concluded once the patient is asked to sit down.

From a modeling perspective, this was also the end of the scope, once the patient sits down their waiting time to be checked-in and their check-in process has been completed and the patient is only waiting to have their visit. One of Organization A's focuses is the impact on receptionist capacity in the Centralized Model based off of this benchmark seen in Table 1. As this waiting time was not considered important as it had no effect on the receptionists and the number of patients waiting for their visit had no impact on patients entering the clinic to be checked-in, once a patient had finished their check-in process it was assumed their clinic visit time had begun. Since this visitation time would most likely include waiting for a doctor or other medical professional and varied widely both internally, as clinics have multiple different processes as well as variation in time for each patient, as well as externally, as times for each clinic were different. To account for this large variation, a patient's visit time is a uniform distribution from one to two hours. This assumption is less accurate to reality than the other time assumptions for the check-in process, but was considered a good general assumption by a member of Organization A.

Once the patient is done with their visit, they either perform the check-out process to schedule a new visit, or they skip the check-out process as they do not want to schedule their next appointment at this time. This concludes their visit to the clinic and the patient has a ten percent chance of being assigned to another clinic. If that patient is assigned to a new clinic, they then leave their current clinic and head directly to the new clinic. An example of the larger table is seen in Table 9. Once the table is read the patient is assigned a number between 1 and 16.

Table 9: Hourly Mixture of Clinics

Clinic	Hour of the Day	Mix
1	1	0
2	1	0
3	1	0.2276
4	1	0
5	1	0
6	1	0.0031
. . .	. . .	
1	2	0.0495

As shown in Figures 44 and 45, the likelihood of each clinic being assigned to varies by the hour of the day. The secondary tables sort through the middle column dependent on the hour of the day, if it is between 6:00 AM and 6:59 AM then the mixture in the third column is used. The mixture correlates to Figures 44 and 45. Once the model reaches 7:00 AM the 16 rows that have 2 for their hour of the day value are the rows being read. The mixtures for those 16 clinics are compared to the total for that hour. For example, if there are 100 arrivals in hour 2 and both clinics 1 and 2 have 10.94% in the mixture column and all other columns have zero, then roughly 50 patients will go to each clinic. Due to this the percentages available from Organization A requires no alteration as the total percentage can change from hour to hour, and the mixture from hour to hour can change as well. This makes it easier to expand in case a certain clinic is opened earlier or stays open later than other clinics. This table besides considering the hourly difference also includes variation in the process to make sure that no two replications are exactly the same. For Organization A the new location was predetermined to be in the first floor of the main hospital.

However, the changes to the process have drastically decreased the check-in process time as shown in Figure 47. The new central admission location process includes the majority of the current check-in steps while the new clinical check-in involves a self-check-in. When the patient first enters the building, they head directly to the central admission location on the first floor of the main hospital. If the patient does not have to go through the Medicaid second payer process and if they have their insurance information readily available then their time at the station is relatively short before heading to their destination clinics where those two steps are excluded and the patient has the option to self-check-in which they will most likely do unless they need assistance.

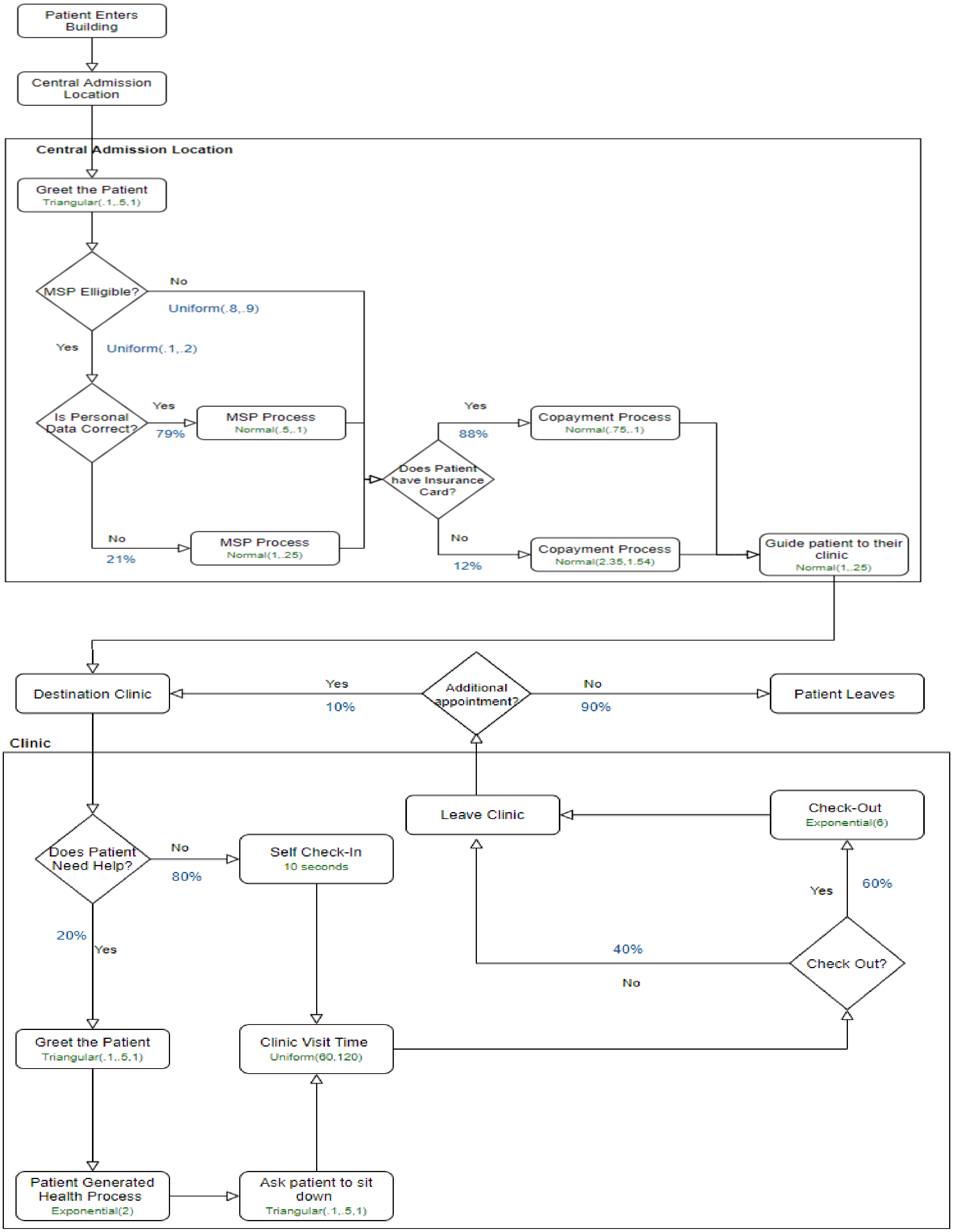

Figure 47: Patient Flow for Centralized Model

The model incorporates the check-in and check-out steps by utilizing add-on processes. The check-in process and check-out process seen in Figures 48 and 49 respectively are a combination of delay and decide steps. The delay steps refer to each time in the process reference a specific table seen in Figure 50. The times in that table are compared to a value of 0 and the larger of those two values are chosen to make sure no steps ever take a negative amount of time. Having the times in this separate table also allows them to be easily changed and applicable to multiple spots as different delay steps can refer to the same column. Similarly, Figure 51 shows the process mixes which are referenced in the decide steps. Those steps refer to a specific column, for example, the is patient info correct step refers to the 2nd column in the process mix table. That then reads the probability of .79 out of 1 and therefore the patient has a 79% chance of having true as the answer and heading to the correct process time delay step. Once again, having the numbers in a separate table made them easier to change which became very useful for running experiments.

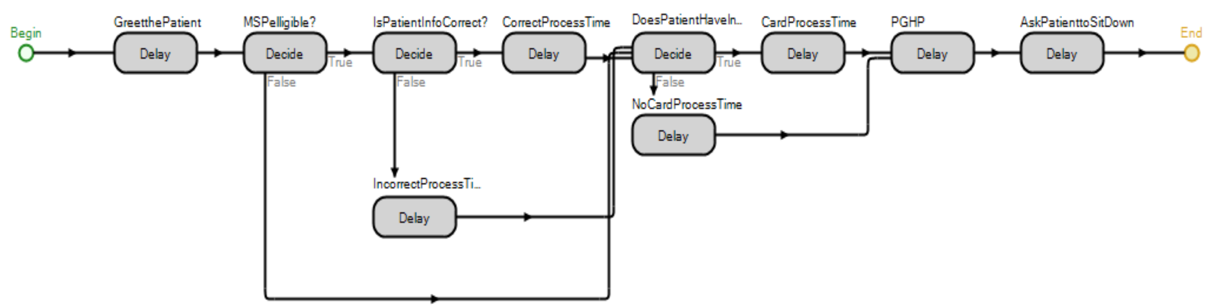

Figure 48: Check-In Add-On Process

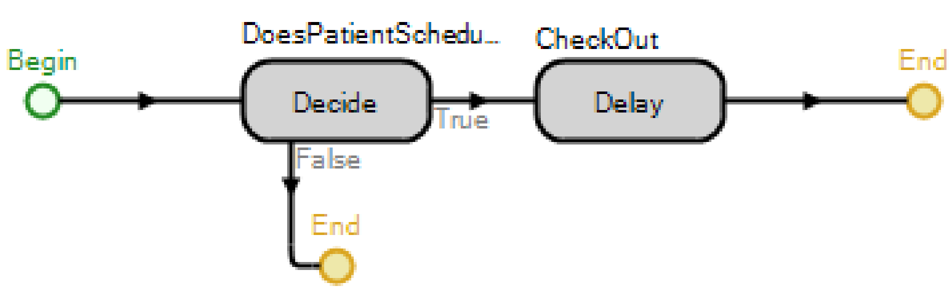

Figure 49: Check-Out Add-On Process

Properties: ProcessTimeTable[1] (Table Row)

General	
GreetThePatient	Math.Max(0,Random.Triangular(.1 ,.5,1))
IncorrectProcessTime	Math.Max(0,Random.Uniform(1,.25))
CorrectProcessTime	Math.Max(0,Random.Normal(.5,.1))
NoCardProcessTime	Math.Max(0,Random.Normal(2.35,1.54))
CardProcessTime	Math.Max(0,Random.Normal(.75,.1))
PGHP	Math.Max(0,Random.Exponential(2))
AskPatienttoSitDown	Math.Max(0,Random.Triangular(.1,.5,1))
CheckOut	Math.Max(0,Random.Exponential(6))

Figure 50: Process Time Table

Properties: ProcessMixTable[1] (Table Row)

General	
MSPelligible	Random.Uniform(.1,.2)
IsPatientInfoCorrect	0.79
DoesPatientHaveInsuranceCard	0.88
DoesPatientScheduleNextVisit	0.6
MultipleAppointment	0.1

Figure 51: Process Mix Table

The centralized patient flow begins with a short trip to the central admission location. Once there the patient has the same decisions as those at the beginning of the decentralized check-in. As the majority of patients skip the Medicare Second Payer (MSP) Process and have the shorter copayment process time, the overall time for the central admission is relatively quick. The information is transferred to the clinic as it is being recorded by the receptionist in the central admission location, which leaves a short check-in process at the destination clinic. Depending on the patient and their personal needs, the patient can either self-check-in or receive assistance from the receptionist. As the percentage of patients who would self-check-in and the self-check-in time are both unknown and there were no methods of testing due to Covid-19, assumptions were made for both with input from a member of Organization A. As seen in Figure 47, the majority of patients will most likely be able to check-in by themselves. If not, the remaining steps from the decentralized check-in are performed by the receptionist. When leaving, the patient has a chance of having another appointment and is rerouted to one of the clinics, with the chances seen in Figure 52 for each clinic.

	Clinic Destination	Clinic Mix	Mix Expression
1	1	3.47	Math.If(ModelEntity.ClinicNumber==1,0,ClinicMix[1].ClinicMix)
2	2	7.06	Math.If(ModelEntity.ClinicNumber==2,0,ClinicMix[2].ClinicMix)
3	3	4.24	Math.If(ModelEntity.ClinicNumber==3,0,ClinicMix[3].ClinicMix)
4	4	8.34	Math.If(ModelEntity.ClinicNumber==4,0,ClinicMix[4].ClinicMix)
5	5	8.09	Math.If(ModelEntity.ClinicNumber==5,0,ClinicMix[5].ClinicMix)
6	6	7.83	Math.If(ModelEntity.ClinicNumber==6,0,ClinicMix[6].ClinicMix)
7	7	10.91	Math.If(ModelEntity.ClinicNumber==7,0,ClinicMix[7].ClinicMix)
8	8	6.55	Math.If(ModelEntity.ClinicNumber==8,0,ClinicMix[8].ClinicMix)
9	9	8.47	Math.If(ModelEntity.ClinicNumber==9,0,ClinicMix[9].ClinicMix)
10	10	5.01	Math.If(ModelEntity.ClinicNumber==10,0,ClinicMix[10].ClinicMix)
11	11	14.89	Math.If(ModelEntity.ClinicNumber==11,0,ClinicMix[11].ClinicMix)
12	12	4.62	Math.If(ModelEntity.ClinicNumber==12,0,ClinicMix[12].ClinicMix)
13	13	2.18	Math.If(ModelEntity.ClinicNumber==13,0,ClinicMix[13].ClinicMix)
14	14	3.08	Math.If(ModelEntity.ClinicNumber==14,0,ClinicMix[14].ClinicMix)
15	15	2.7	Math.If(ModelEntity.ClinicNumber==15,0,ClinicMix[15].ClinicMix)
16	16	2.57	Math.If(ModelEntity.ClinicNumber==16,0,ClinicMix[16].ClinicMix)

Figure 52: Clinic Mix Table

The new central check-in process is modeled in Figure 53 as an add-on process. This process is completed by each patient, though the majority skip the Medicare Second Payer Process and the total maximum time for this process is lower than that of the total maximum time for the decentralized check-in process. Once this process is completed the patient heads to their next clinic.

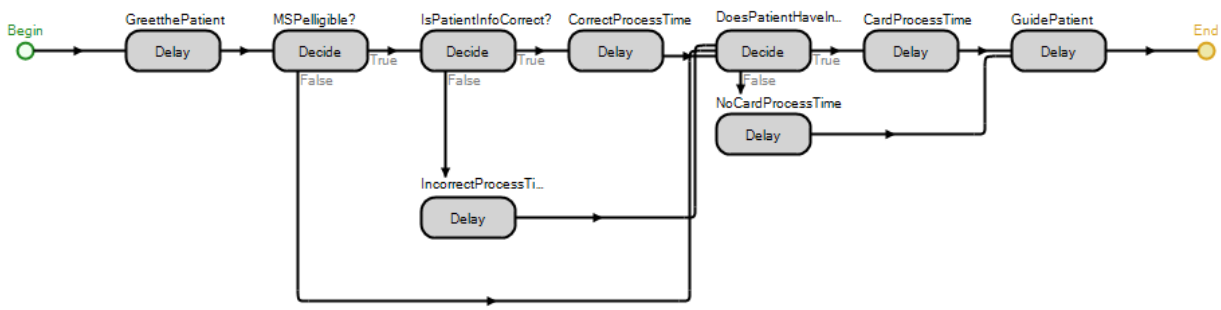

Figure 53: Central Check-In Add-On Process

As the patient heads to their destination clinic they have a decision to make on whether they require help checking-in or if they can perform the self-check-in as shown in Figure 54. The difference between the two times is larger, though the maximum total time for the clinical check-in is far less than the time it took in the decentralized model.

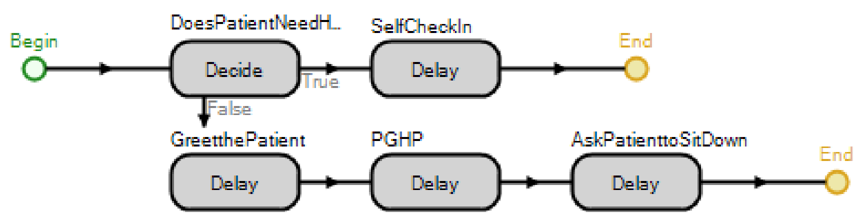

Figure 54: Central Check-In Add-On Process

6.4 Validation Model Outputs

The metrics for both systems were the same, with the primary focus on the throughput of patients through each system, the clinical wait time, and the patient wait time. These metrics were gathered in the same manner as the general models for the experiments. Of those three, the wait times were emphasized over the throughput as the general experiments before revealed that the throughput ratio was generally constant across all scenarios, even if wait time fluctuated greatly.

6.5 Validation Decentralized and Centralized Experiments

As the staffing for the centralized model has been determined we can run both systems to compare the two and determine the advantages and disadvantages of each system. The experiments above gave some idea about which system would be best suited for Organization A. Organization A has around 779 patients per day, though like most healthcare organizations they have experienced fluctuating demands. The experiments on arrival rate tables show that the centralized system works better especially in higher demand days for both average clinical wait time and patient wait times. The average arrival rate proved a murkier setting with no clear victor.

The disparity between clinics in Organization A does not perfectly match a single scenario from the disparity experiments, as one clinic has the highest demand by a large margin but the remaining clinics are somewhat equally split into the 50-60 patients range or the 20-30 patients' range. This is different than in the experiments where the remaining clinics all fell into one equal distribution. However, since Organization A has one larger clinic it would indicate that the centralized system may be better suited, as the disparity experiments showed that the central admission location served as a key buffer.

Patients in Organization A's facilities have a ten percent chance of having multiple appointments across the clinics. As the lower spectrum of percentages showed little impact by the multiple appointment patients and no clear winner between the two systems.

Travel Time would appear to not be a deciding factor in which system is best suited for Organization A as the initial travel time in the decentralized model falls under the scope of patient travel time. The differences in patient wait time between the two are therefore equally impacted by the travel time which makes its overall impact as a deciding factor insignificant.

Finally, Organization A is on the larger end of the spectrum of the number of clinics tested. This would indicate that a centralized approach is better as the shorter process time for the central check-in and handoff procedure allow for quicker wait times on average, though the maximum wait times may be slightly larger.

Overall, these factors show an equal choice between the systems due to arrival rate, multiple appointment patients, and travel time, but show a centralized approach would be better suited for Organization A’s clinical mixture disparity and large number of clinics. Whether these two last factors cause the centralized system to be the best overall must be tested. The current state staffing was used for the decentralized model and staff level 2 for the centralized model. The percentage of multiple appointment patients was kept at ten percent, and travel times were not increased. The current state clinical mixture for rerouting and by hour of admission was used for both models. The results of 300 replications were compiled and are shown in Figure 55 which shows the clinical wait time values.

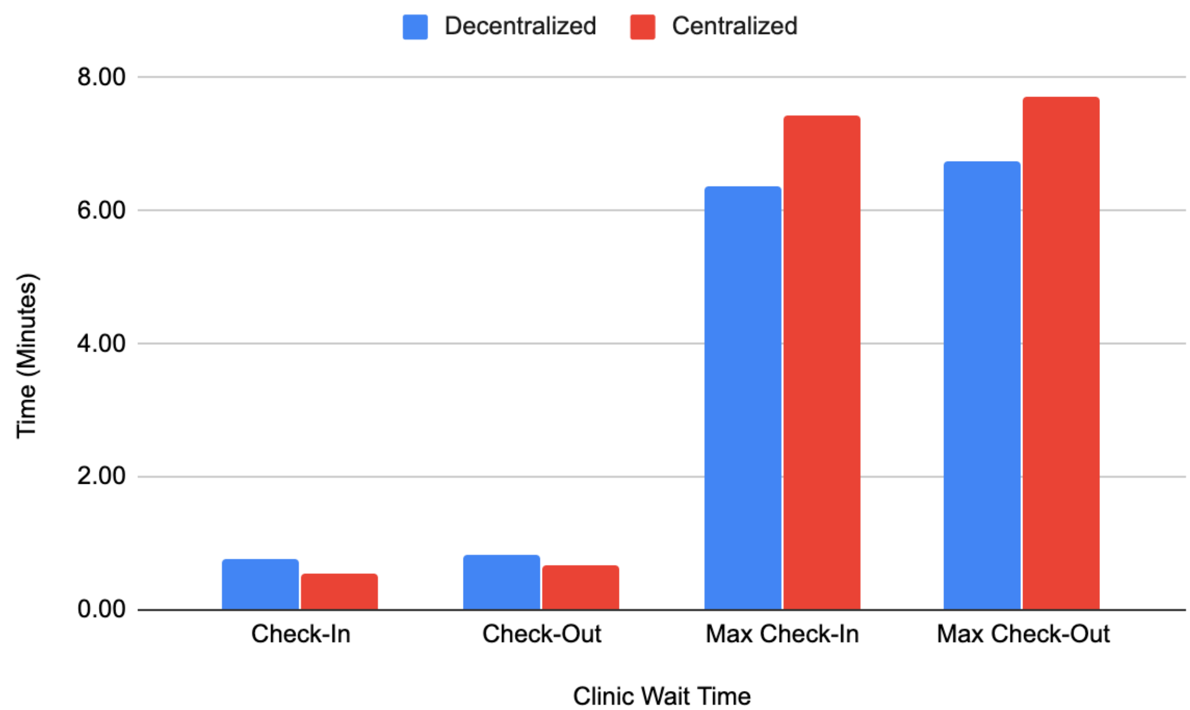

Figure 55: Clinical Wait Times for the Two Models

This continues the tendency for the centralized system to perform better on average but to still have higher maximum wait times. In both regards, the difference is not large enough to indicate one clear choice, which is reiterated in Figures 56 and 57 which show the average patient waiting time and maximum patient waiting time repetitively.

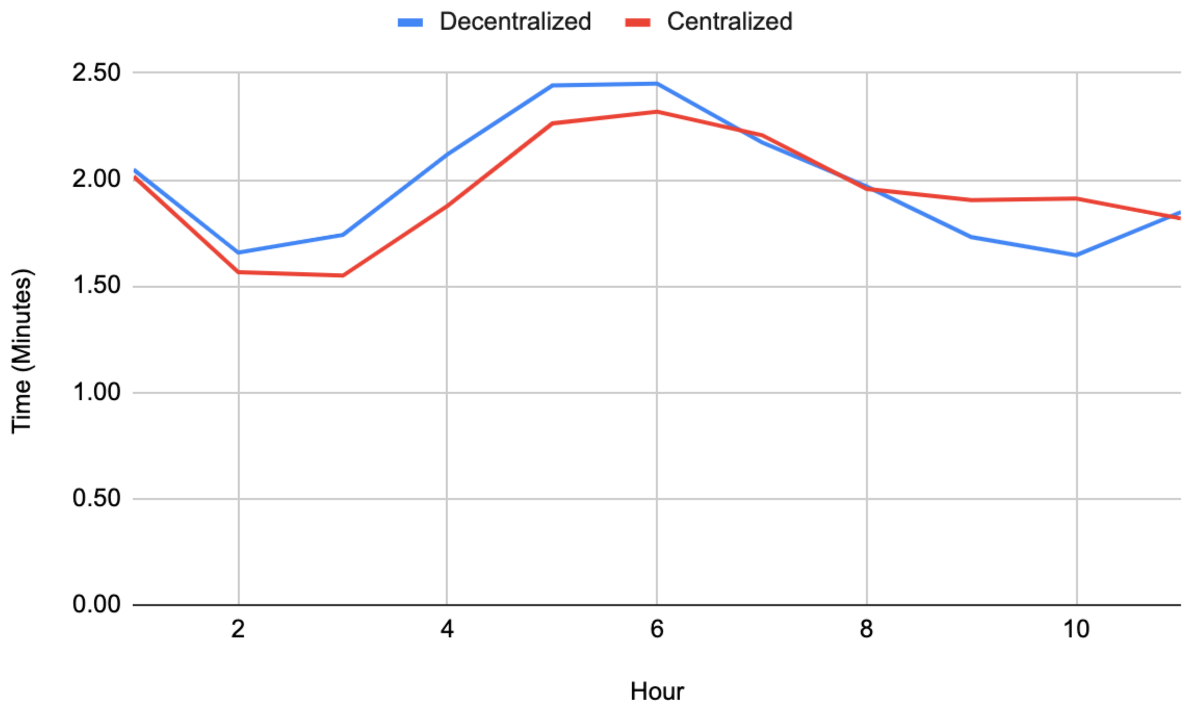

Figure 56: Average Patient Wait Times for the Two Models

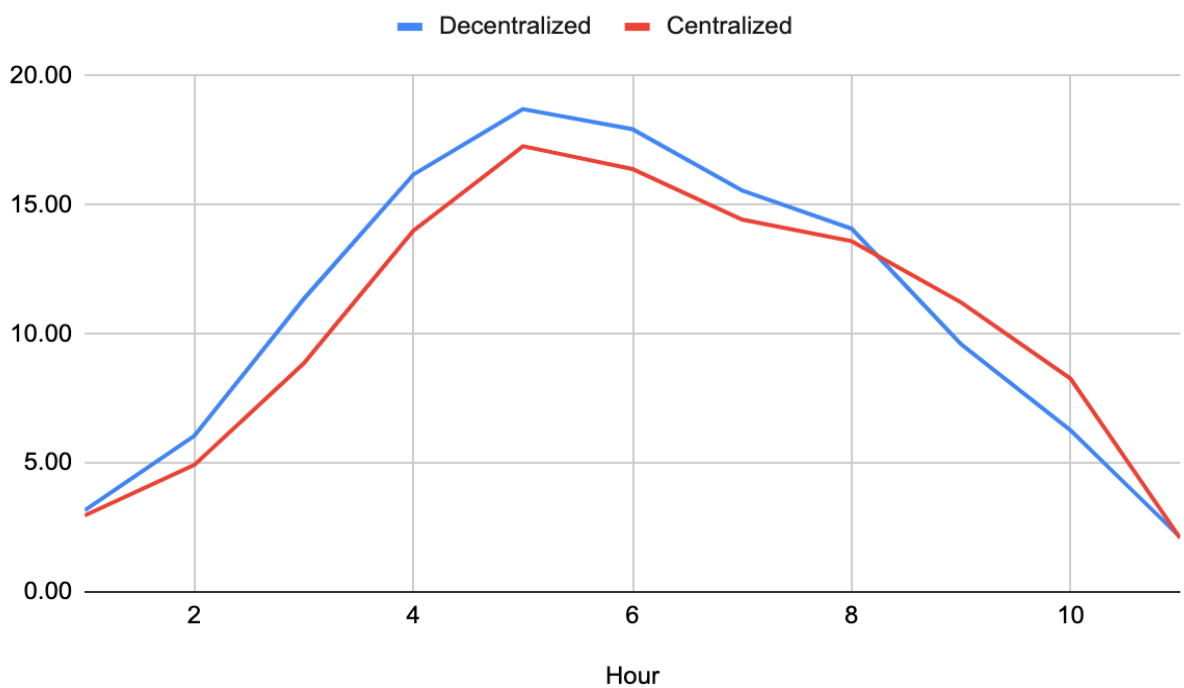

Figure 57: Maximum Patient Wait Times for the Two Models

The full results of the decentralized and centralized runs are seen in Tables A27 and A28 in the appendix. All differences are significant except for the maximum patient wait times between hour 8 and hour 11. These results validate the initial assumptions made based on the general experiments which are that the decentralized and centralized would perform generally the same with some factors favoring centralization. This is seen with the centralized system having a smaller average clinic wait time and overall a smaller average and maximum patient wait time compared to the decentralized model. Unless Organization A finds the maximum clinical wait time to be the most important metric then it would appear the centralized approach is the better choice. The centralized system reduces the staffing capacity needed by 6 to have these results that are equal or better than the current state decentralized model.

7 Conclusion

Both the general experiments and validation experiment gave a greater understanding of the strengths and weaknesses of the decentralized and centralized approaches over different factors. While the general experiments examined the effect of each factor individually the validation model gave insight on the effect of the combination of factors and which may be the most influential for the decision.

7.1 Thesis Limitations

The thesis model faced several limitations, especially due to the covid-19 pandemic. The primary limitation was due to the COVID-19 pandemic. Due to the pandemic, time studies could not be performed at Roswell and so time assumptions were made based on similar processes (Chand, 2009). These times were validated by a member of Roswell who also gave time estimates for specific processes to Roswell that had no comparable time in literature. The centralized check-in and handoff procedures are also both estimates based on the initial estimates. As the decentralized check-in process is the current state the estimates were easier to arrive at, but both the centralized processes are not currently done and so it is unknown if splitting the decentralized steps would change the amount of time each step takes in the centralized process. It was assumed that the process time for a step would remain unchanged whether it was in a decentralized clinic or at the central admission location. Observing the processes may have also revealed additional factors, process steps, or patient types that should be examined in the scope. As mentioned before there are also uncaptured miscellaneous processes that receptionists perform, primarily when no one is being checked-in or checked-out. Capturing these additional steps would give a better overall view of receptionist utilization but were not able to be timed due to pandemic restrictions. Travel times were another large estimate, based on the estimation tool and not real-world recorded values. The travel time and facilities layout could have been examined in more detail had visits to Roswell been possible.

Due to time restrictions, while making the models and examining the results, larger intervals were chosen for the factors. Some benefit may be derived by going into more detail, such as for the number of clinics experiment by increasing by an interval of 1. Ranges were also created using real-world data from Roswell Cancer Clinic Institute instead of, for example, going to an organization with 4 or 8 clinics for the low number of clinics experiment. It is important to realize that the data used is derived from one source and so may not be entirely comparable to other organizations that may spend more or less time on the same processes.

7.2 Validation Decentralized and Centralized Experiment Conclusions

While the differences between the two systems may seem somewhat arbitrary they are statistically significant. They show that on average the centralized system performs better, especially during the earlier hours, even once the peak is reached. After this, the decentralized system seems to perform better for patient wait time and maximum clinic wait time. However, since the maximum patient wait times for hours 8, 9, and 10 are statistically insignificant, the gap in Figure 56 for those hours is overstated. The lack of definitive proof that one of these systems was better for Organization A's needs was what was expected given most of the individual factors, with the centralized system performing better as the other factors implied. Then the centralized system's weaknesses became more visible as the descent from the peak was more gradual than the decentralized model.

The overall results of the centralized and decentralized systems show that the centralized system is slightly better for Organization A's needs overall. Further reductions to the centralized system's clinical wait time and patient wait times can be made by increasing staff if wanted. For Organization A the deciding factor may be the financial savings associated with the centralized system compared with the cost of transitioning to a centralized approach from the current state. Whether the reduction in staffing needs and average wait times is worth the cost of setting up a central admission location is a decision for Organization A.

7.3 General Decentralized and Centralized Experiment Conclusions

The experiments show that there is no clear victor between the decentralized and centralized models as both have strengths and weaknesses depending on the conditions of the healthcare organization being modeled. An overview of the factors and which system they are best suited for, if any, is shown in Figure 58.

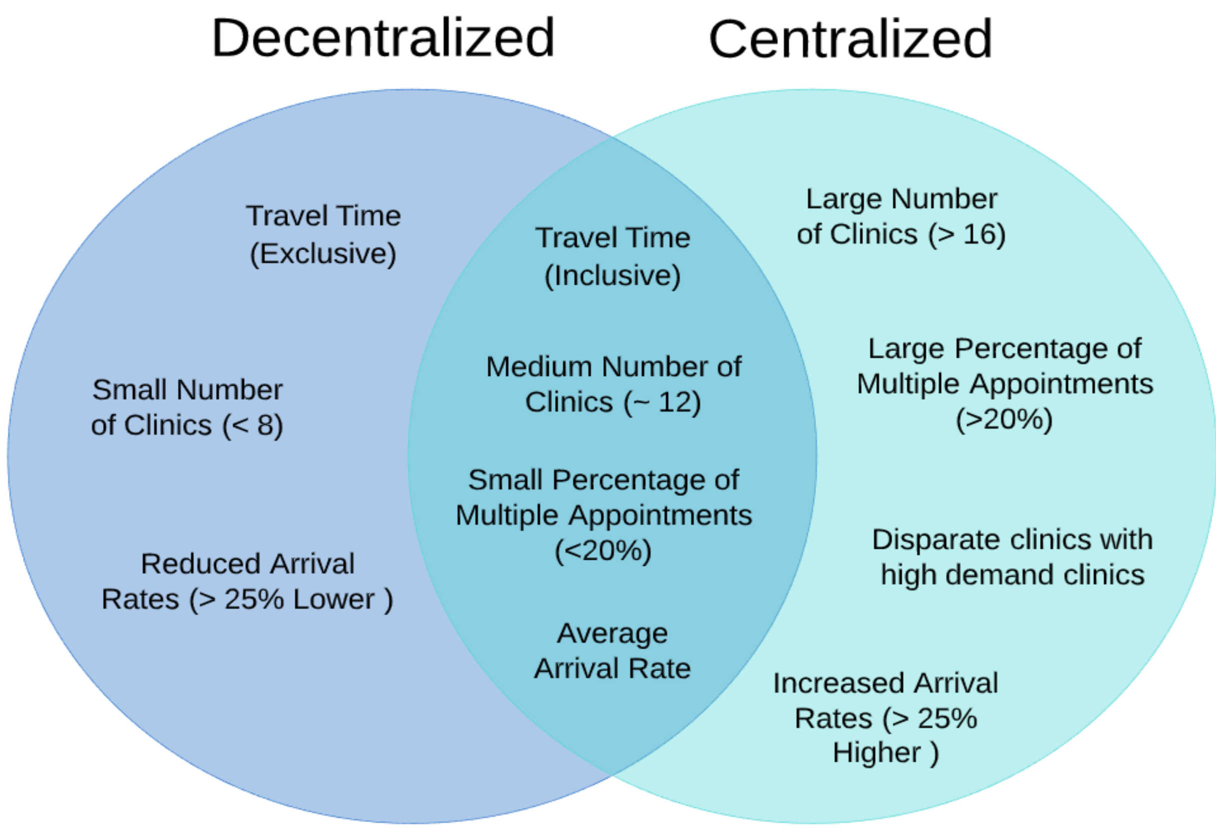

Figure 58: Venn Diagram of Conditions

There are certain elements that best suite a decentralized approach, primarily for fewer clinics that have smaller demands or clinics that are located farther away from each other. While Organization A had all of its patients enter through the main lobby in two combined buildings, other organizations may have their clinics spread across non-adjacent clinics. In those cases, there is not a central starting point for the patients. A key reason why the centralized system did not have practically larger patient wait times as travel time increased was that all patients already started at the same point before going to the central admission location. For more distantly located clinics, this would require all patients going to one location for the central admission location before either walking or driving to another location. If parking is involved this can drastically increase the time. In a centralized system, this time would have to be accounted for as it is the result of the central admission location, whereas for a decentralized system the patient heads directly to their first appointment and the time it takes to get to the building may be considered an accepted time for the patient. For example, the time it takes the patient to get to the main lobby in Organization A was accepted as out of scope, though some patients may be 5 minutes away while others are 50 minutes away. Excluding this initial travel time would solely benefit the decentralized system and would make it the clear choice if that is the only factor being considered.

Another scenario that would benefit a decentralized approach is a small number of clinics, though this is primarily due to the weakness of a centralized approach in this situation. As the decentralized system generally has a smaller maximum clinical wait time, having fewer clinics will benefit the decentralized system as the centralized system would be more influenced by outliers caused by spikes in admission. Related to that, if arrival rates are the only factor being changed then the decentralized system benefits from a reduced arrival rate as otherwise, its staffing must be far greater than the centralized model. With reduced arrivals, the benefit of the handoff procedure is minimized and the extra step of going through the central admission location becomes less beneficial.

If travel time includes the initial travel to the first appointment then either system may perform best regardless of the distance between clinics. For most factors, there is the decision between a higher maximum wait time and a lower average wait time if the healthcare organization clinic transitions from a decentralized system to a centralized system. This is seen if the number of clinics is between 8 and 16 clinics if the process times are comparable to those of Organization

A. This is also similar if the number of patients that have multiple appointments is 10 percent or less, and debatably for when the likelihood is 20 percent. For an average arrival rate, the decision is also dependent on whether more emphasis is placed on the average or maximum wait times.

A centralized approach can work best for other conditions, as a system it works better for the increased rate tables given that the central admission location is adequately staffed. There are some weaknesses, especially associated with staffing. As the change reduces the amount of time spent at each clinic on average, the staffing for those clinics can be reduced. However, in scenarios where those clinics are now faced with a sudden increased demand due to either the arrival rate or clinic mixture, then the maximum wait times for those clinics will exceed the decentralized version and will impact the overall centralized system performance as well as patient satisfaction. Another key aspect of staffing is the central admission location, which can become a bottleneck if not adequately handled.

A centralized system also has a better buffer for higher demand clinics in high disparity systems the reduced clinic check-in time limits the effect of the disparity between high and low demand clinics. While for other factors the best performance for the average and maximum wait times are split between the two systems, high percentages of multiple appointment patients have both clinical and patient wait times that are shorter than in the centralized model compared to the decentralized system. The centralized system performs better than the decentralized system as the number of clinics increase, as the shorter process times allows for most patients to have short wait times and the average wait times impact the overall performance more than the few maximum outliers that are higher in the centralized system than the decentralized system.

These results also show the weaknesses of a centralized approach, which is higher maximum clinical wait times and a slower descent from the peak patient wait times. While the centralized model performs overall, an organization choosing in this scenario must make two key decisions. The first is whether to place more importance on the average wait time or on the maximum wait time. Is the goal making the process faster for the average patient or reducing the worst-case scenario time for patients? There is no one correct answer to this and depends on the times the organization considers acceptable. The second decision to be made is the importance of the staffing change between the two models, the centralized system can achieve similar results to the decentralized system by a reduction in staff that can be very large dependent on the factors of clinic number and arrival rates. Once these decisions are made, the difficult process of implementing the best admission system can begin and hopefully result in better waiting times for patients.

7.4 Future Work

A possible expansion of this thesis is to examine separate patient types, especially the registration process for new patients. For Roswell, this process was being considered about whether to be included in the scope of the model but was eventually excluded as it did not have an impact on the rest of the admission process. However, there are certain cases where this unique patient process may be more involved in the design of a centralized system. In Roswell registration is located separately from the other clinics, but in creating a central admission location there is now an opportunity to combine the two processes into one location. Therefore, new patients would have to only go to the central admission location to go through both the registration and check-in processes. There might also be space savings or reduction in overall staffing. How exactly both processes could be performed at the same location and the necessary design and process flows would be an interesting thesis that would examine many of the same metrics and inputs as this thesis.

Instead of gathering all real-world data from one large healthcare organization, gathering data directly from varying size clinics would be very useful. The small number of clinic models were based on Roswell's current state absent a few clinics, but getting data from smaller clinics would be useful as well as data from consolidated clinics that are located farther apart. This could result in testing similar conditions to this thesis but in greater ranges or more detailed intervals to further examine the conditions that benefit each condition.

The handoff procedure modeled is an estimation of a future process and so further work can be done to determine the best handoff procedure for a centralized clinic. By testing different handoff procedures in similar conditions, the effectiveness of each approach can be examined before implementing a centralized system, allowing for the best practice to be selected first.

One of the initial goals was to go into more detail into facilities planning, especially regarding the number of seats and space for each clinic and the central admission location. This became impossible due to the pandemic and overall was generally out of scope for the thesis, but would be useful for the implementation of the centralized system in the real world, and the physical restrictions or changes needed to accomplish it.

This thesis can also be expanded on either examining different conditions than used in the experiments, or by testing two-level factorial experiments of the factors in the thesis. This would result in a greater understanding of the relationship and interconnectedness of the factors, as well as determining which of the factors are the most important when considering the change.

Finally, the last possible suggestion for expansion is a result of the uncertainty the healthcare industry has faced in the last few trying months. Generally, we have seen an increase in telehealth appointments to adapt to the new pandemic concerns. Examining the effect of adopting telehealth either briefly or permanently would require an in-depth analysis of many aspects of clinics and other healthcare-related facilities, and the decentralized and centralized admission may have a place in that discussion.

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Appendix

(All Times are in Minutes)

A.1 Hourly Likelihood

Table A1 shows the percent likelihood for each clinic that a patient arriving each hour will have that clinic as their destination. Each column is equal to 100%

Table A1: Hourly Likelihood for Clinic Assignment

Clinic #	6:00 AM	7:00 AM	8:00 AM	9:00 AM	10:00 AM	11:00 AM	12:00 PM	1:00 PM	2:00 PM	3:00 PM	4:00 PM	5:00 PM
1	0.00%	4.95%	3.99%	3.30%	3.24%	2.43%	3.19%	3.96%	3.78%	3.62%	0.65%	11.59%
2	0.00%	0.66%	5.61%	8.27%	8.56%	8.44%	7.93%	7.83%	7.12%	4.56%	1.33%	5.56%
3	22.76%	9.47%	4.11%	3.23%	3.47%	5.12%	3.97%	3.52%	2.70%	2.65%	2.21%	0.00%
4	0.00%	10.90%	9.19%	8.36%	7.05%	8.46%	8.41%	8.10%	8.52%	9.20%	3.83%	0.00%
5	0.00%	8.51%	9.20%	7.91%	8.24%	9.26%	7.75%	7.36%	7.45%	6.98%	3.89%	6.37%
6	0.31%	6.20%	7.24%	7.31%	7.96%	8.08%	9.20%	8.11%	8.66%	9.04%	10.14%	6.16%
7	0.00%	9.25%	12.48%	10.49%	9.91%	7.29%	11.01%	13.17%	14.78%	13.11%	6.38%	0.00%
8	0.00%	0.45%	5.97%	7.60%	8.16%	5.48%	5.58%	7.34%	7.86%	10.09%	6.43%	0.00%
9	0.00%	4.89%	8.25%	7.78%	9.25%	9.32%	9.26%	8.35%	9.51%	11.10%	7.79%	0.00%
10	0.00%	2.72%	4.71%	5.37%	4.99%	4.14%	6.37%	5.95%	5.70%	3.85%	5.23%	0.00%
11	74.44%	29.75%	13.82%	13.00%	13.29%	15.08%	14.25%	10.71%	10.55%	12.45%	45.10%	70.32%
12	0.32%	1.72%	4.28%	5.05%	4.65%	6.33%	5.50%	4.41%	3.83%	4.66%	3.19%	0.00%
13	0.00%	2.97%	2.70%	2.70%	2.21%	1.99%	1.98%	1.91%	1.30%	1.01%	0.64%	0.00%
14	0.00%	0.00%	2.42%	3.31%	3.21%	3.91%	1.04%	4.65%	4.69%	5.43%	2.57%	0.00%
15	0.85%	3.75%	2.10%	3.11%	3.51%	3.07%	2.92%	2.37%	1.34%	0.67%	0.62%	0.00%
16	1.33%	3.81%	3.92%	3.20%	2.31%	1.58%	1.64%	2.25%	2.19%	1.58%	0.00%	0.00%

A.2 Staffing Results

Tables A2 to A5 show the results of running different staffing levels in the centralized model to determine the best comparable staffing level.

Table A2: Wait Times for Centralized Clinic Receptionist Levels (In Minutes)

	Check-In				Check-Out			
Recs	**Sum Avg**	**Sum Max**	**Avg**	**Max**	**Sum Avg**	**Sum Max**	**Avg**	**Max**
1	89.56	458.47	5.60	28.65	108.37	465.69	6.77	29.11
2	6.03	90.29	0.38	5.64	7.07	92.59	0.44	5.79
3	0.64	20.53	0.04	1.28	0.75	21.23	0.05	1.33
4	0.09	4.12	0.01	0.26	0.10	4.08	0.01	0.26

Table A3: Wait Times for Centralized Clinic Receptionist Levels (In Minutes)

	Check-In				Check-Out			
Recs	**Sum Avg**	**Sum Max**	**Avg**	**Max**	**Sum Avg**	**Sum Max**	**Avg**	**Max**
1	362.10	956.46	22.63	59.78	441.02	977.13	27.56	61.07
2	26.87	158.77	1.68	9.92	29.17	164.68	1.82	10.29
3	3.20	45.79	0.20	2.86	3.40	47.41	0.21	2.96
4	0.56	15.07	0.04	0.94	0.60	15.94	0.04	1.00

Table A4: Wait Times for Centralized Staff 1 Receptionist Levels

Clinic	Receptionists	Average Check-In Wait Time	Maximum Check-In Wait Time	Average Check-Out Wait Time	Maximum Check-Out Wait Time
1	1	1.50	14.61	1.76	15.03
2	2	0.43	7.12	0.51	7.26
3	2	0.10	2.20	0.12	2.40
4	2	0.49	8.38	0.54	8.24
5	2	0.54	8.66	0.61	8.45
6	2	0.47	8.39	0.53	8.32
7	2	0.98	12.33	1.18	12.48
8	2	0.30	5.92	0.40	6.45
9	2	0.60	9.28	0.72	9.61
10	2	0.18	3.84	0.20	4.03
11	2	1.78	17.01	2.04	16.95
12	2	0.17	3.46	0.19	3.55
13	1	0.90	8.61	1.09	9.44
14	1	1.32	12.64	1.69	14.09
15	1	1.27	12.20	1.46	12.06
16	1	1.12	11.79	1.50	12.63
Central	6	0.71	5.62	N/A	N/A

Table A5: Wait Times for Centralized Staff 2 Receptionist Levels

Clinic	Receptionists	Average Check-In Wait Time	Maximum Check-In Wait Time	Average Check-Out Wait Time	Maximum Check-Out Wait Time
1	2	0.08	1.60	0.08	1.67
2	2	0.40	7.26	0.51	7.55
3	2	0.10	2.31	0.10	2.22
4	2	0.44	7.89	0.48	7.45
5	2	0.46	7.98	0.54	8.32
6	2	0.46	7.58	0.52	7.93
7	2	0.81	11.37	1.00	11.89
8	2	0.33	6.59	0.39	6.39
9	2	0.61	9.45	0.73	9.66
10	2	0.16	3.59	0.18	3.80
11	3	0.26	6.14	0.29	6.18
12	2	0.15	3.16	0.17	3.29
13	1	0.90	8.57	1.02	9.41
14	1	1.34	12.59	1.72	13.96
15	1	1.19	11.64	1.41	11.80
16	1	1.12	11.00	1.41	11.96
Central	6	0.69	5.49	N/A	N/A

A.3 Results and Confidence Intervals of General Experiments

Tables A6 to A26 show both the results in terms of average wait times and average maximum wait times across the replications for each experiment, as well as the confidence intervals for the experiments. Figures A1, A2, and A3 all show the maximum times that were excluded in the experiments section.

Table A6: Results of Rate Table Experiments for the Decentralized Model

Decentralized	Setup	Summary	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
		Arrival Rate Table	Hourly Arrival Mean	25% Higher	50% Higher	25% Lower	50% Lower
	Throughput	Patients Entered	781.51	975.41	1094.51	728.99	548.03
		Patients Left	771.47	962.85	1080.61	719.41	541.24
		Ratio	98.71	98.71	98.73	98.69	98.76
		Average Number in System	121.85	154.19	174.95	113.21	84.77
		Std. Dev Patients Entered	25.80	28.99	31.78	27.41	25.41
Clinical Wait Time	Check In	Average	0.77	1.32	1.77	0.67	0.40
		Max	6.38	9.07	10.89	5.65	3.65
	Check Out	Average	0.83	1.42	1.92	0.70	0.43
		Max	6.75	9.49	11.38	6.00	3.88
Patient Wait Time	Hour 1	Average	2.05	2.07	2.07	2.04	2.03
		Max	3.16	3.53	3.47	3.09	2.87
	Hour 2	Average	1.66	1.88	1.83	1.65	1.60
		Max	6.05	9.37	9.89	5.82	4.71
	Hour 3	Average	1.74	2.09	2.17	1.68	1.58
		Max	11.36	17.28	20.45	10.03	7.18
	Hour 4	Average	2.12	2.88	3.24	2.04	1.75
		Max	16.17	23.24	27.67	14.47	10.70
	Hour 5	Average	2.44	3.60	4.27	2.31	1.90
		Max	18.72	27.11	32.21	17.69	12.89
	Hour 6	Average	2.45	3.73	4.88	2.23	1.91
		Max	17.94	26.33	33.11	15.74	11.86
	Hour 7	Average	2.17	3.06	4.19	1.97	1.76
		Max	15.56	21.59	29.63	13.19	9.84
	Hour 8	Average	1.97	2.46	3.20	1.87	1.68
		Max	14.08	19.09	25.44	12.76	9.18
	Hour 9	Average	1.73	2.01	2.40	1.71	1.58
		Max	9.60	13.25	17.07	9.04	6.80
	Hour 10	Average	1.64	1.73	1.96	1.67	1.59
		Max	6.26	7.39	10.59	6.38	4.57
	Hour 11	Average	1.85	1.80	1.95	1.83	1.63
		Max	2.12	2.24	2.51	2.07	1.80

Table A7: Results of Rate Table Experiments for the Centralized Model

Centralized	Setup	Summary	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
		Arrival Rate	Hourly Arrival Mean	25% Higher	50% Higher	25% Lower	50% Lower
	Throughput	Patients Entered	778.61	973.50	1095.72	727.87	551.15
		Patients Left	769.01	961.57	1079.13	718.71	544.29
		Ratio	98.77	98.77	98.49	98.74	98.76
		Average Number in System	121.34	161.42	203.04	112.92	84.90
		Std. Dev	27.85	30.96	34.29	25.66	24.07
Clinical Wait Time	Check In	Average	0.55	0.86	0.99	0.49	0.30
		Max	7.42	10.14	11.15	6.81	4.40
	Check Out	Average	0.66	0.98	1.15	0.61	0.38
		Max	7.72	10.26	11.45	7.16	4.74
	Central	Average	0.69	7.10	20.91	0.39	0.08
		Max	5.49	23.41	44.71	4.11	2.09
Patient Wait Time	Hour 1	Average	2.02	2.02	2.03	2.00	1.97
		Max	2.96	3.07	3.12	2.92	2.81
	Hour 2	Average	1.56	1.57	1.59	1.55	1.55
		Max	4.92	5.23	6.26	4.41	4.04
	Hour 3	Average	1.55	1.62	1.68	1.54	1.50
		Max	8.86	11.48	13.00	8.31	6.36
	Hour 4	Average	1.88	2.12	2.29	1.82	1.70
		Max	14.00	17.85	20.45	12.60	9.82
	Hour 5	Average	2.26	2.71	2.72	2.15	1.86
		Max	17.28	21.66	22.24	16.39	12.39
	Hour 6	Average	2.32	2.70	2.76	2.25	1.93
		Max	16.40	19.68	20.63	15.09	11.37
	Hour 7	Average	2.21	2.63	2.74	2.15	1.81
		Max	14.43	18.59	19.43	14.45	10.18
	Hour 8	Average	1.96	2.60	2.76	1.91	1.71
		Max	13.60	18.84	19.82	12.24	9.64
	Hour 9	Average	1.90	2.33	2.89	1.86	1.68
		Max	11.22	15.25	18.08	10.13	7.93
	Hour 10	Average	1.91	2.16	2.60	1.80	1.65
		Max	8.27	10.54	13.48	7.46	5.19
	Hour 11	Average	1.82	1.88	2.29	1.78	1.89
		Max	2.09	2.26	2.92	2.09	2.14

Table A8: Confidence Intervals of Rate Table Experiments for the Decentralized Model

Decentralized	Setup	Summary	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
		Arrival Rate Table	Hourly Arrival Mean	25% Higher	50% Higher	25% Lower	50% Lower
Clinical Wait Time	Check In	Average	(.70,.82)	(1.22,1.43)	(1.64,1.90)	(.62,.74)	(.36,.44)
		Max	(5.92,6.70)	(8.61,9.61)	(10.37, 11.49)	(5.34, 6.08)	(3.31,3.92)
	Check Out	Average	(.74,.88)	(1.32,1.55)	(1.76,2.06)	(.65,.77)	(.38,.47)
		Max	(6.22,7.05)	(9.08, 10.10)	(10.79, 11.94)	(5.65, 6.42)	(3.51,4.15)
Patient Wait Time	Hour 1	Average	(2.02,2.08)	(2.03,2.08)	(2.04,2.09)	(2.01,2.07)	(2.01,2.06)
		Max	(3.06,3.25)	(3.37,3.62)	(3.33,3.69)	(2.99,3.15)	(2.84,2.95)
	Hour 2	Average	(1.65,1.69)	(1.85,1.90)	(1.81,1.86)	(1.64,1.68)	(1.57,1.61)
		Max	(5.93,6.63)	(9.33,10.61)	(9.13, 10.33)	(5.63,6.16)	(4.44,4.86)
	Hour 3	Average	(1.71,1.75)	(2.05,2.11)	(2.12,2.20)	(1.66,1.70)	(1.56,1.59)
		Max	(10.54, 11.65)	(16.31, 17.85)	(19.40, 21.21)	(9.48, 10.55)	(6.76,7.51)
	Hour 4	Average	(2.09,2.17)	(2.81,2.96)	(3.12,3.29)	(2.03,2.10)	(1.75,1.79)
		Max	(15.18, 16.51)	(22.74, 24.52)	(25.85, 27.84)	(14.25, 15.47)	(10.25, 11.37)
	Hour 5	Average	(2.37,2.47)	(3.47,3.69)	(4.14,4.39)	(2.27,2.36)	(1.87,1.92)
		Max	(17.68, 19.16)	(26.56, 28.82)	(30.98, 33.31)	(16.75, 18.30)	(11.83, 13.15)
	Hour 6	Average	(2.35,2.49)	(3.61,3.87)	(4.67,5.02)	(2.21,2.33)	(1.87,1.96)
		Max	(16.91, 18.63)	(25.98, 28.20)	(31.54, 34.13)	(15.26, 16.79)	(10.93, 12.32)
	Hour 7	Average	(2.08,2.18)	(2.92,3.17)	(4.00,4.36)	(1.96,2.05)	(1.72,1.78)
		Max	(14.06, 15.61)	(20.64, 22.74)	(28.33, 30.79)	(12.58, 13.87)	(9.05, 10.35)
	Hour 8	Average	(1.95,2.04)	(2.39,2.55)	(3.13,3.37)	(1.85,1.93)	(1.67,1.72)
		Max	(13.73, 15.27)	(18.21, 20.18)	(24.70, 27.02)	(12.25, 13.63)	(8.81,9.92)
	Hour 9	Average	(1.70,1.76)	(1.91,2.05)	(2.33,2.49)	(1.68,1.74)	(1.55,1.60)
		Max	(9.12, 10.30)	(12.23,13.77)	(16.63, 18.50)	(8.65,9.88)	(6.29,7.21)
	Hour 10	Average	(1.61,1.69)	(1.70,1.79)	(1.90,2.01)	(1.61,1.68)	(1.54,1.62)
		Max	(5.83,6.83)	(7.14,8.30)	(9.79, 11.15)	(5.46,6.39)	(4.18,4.90)
	Hour 11	Average	(1.73,1.92)	(1.69,1.86)	(1.81,2.03)	(1.70,1.89)	(1.59,1.76)
		Max	(1.96,2.18)	(2.10,2.40)	(2.29,2.71)	(1.93,2.15)	(1.75,1.95)

Table A9: Confidence Intervals of Rate Table Experiments for the Centralized Model

Centralized	Setup	Summary	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
		Arrival Rate Table	Hourly Arrival Mean	25% Higher	50% Higher	25% Lower	50% Lower
Clinical Wait Time	Check In	Average	(.50,.61)	(.78,.92)	(.89,1.04)	(.44,.54)	(.26,.34)
		Max	(6.91,7.91)	(9.51,10.65)	(10.50, 11.67)	(6.27,7.24)	(3.93,4.77)
	Check Out	Average	(.60,.72)	(.90,1.07)	(1.06,1.23)	(.54,.66)	(.32,.42)
		Max	(7.22,8.22)	(9.70,10.85)	(10.85, 12.03)	(6.57,7.54)	(4.23,5.10)
Patient Wait Time	Hour 1	Average	(2.00,2.04)	(2.01,2.05)	(2.00,2.04)	(1.98,2.03)	(1.96,2.02)
		Max	(2.92,3.01)	(3.04,3.18)	(3.06,3.18)	(2.87,2.95)	(2.76,2.86)
	Hour 2	Average	(1.55,1.57)	(1.55,1.58)	(1.57,1.60)	(1.54,1.57)	(1.54,1.57)
		Max	(4.58,5.07)	(4.91,5.39)	(5.71,6.43)	(4.29,4.61)	(3.93,4.21)
	Hour 3	Average	(1.54,1.56)	(1.60,1.63)	(1.65,1.68)	(1.52,1.55)	(1.48,1.50)
		Max	(8.24,9.29)	(10.69,12.01)	(12.13, 13.33)	(7.67,8.67)	(5.93,6.74)
	Hour 4	Average	(1.85,1.90)	(2.08,2.14)	(2.23,2.30)	(1.80,1.84)	(1.68,1.71)
		Max	(13.37,14.65)	(16.96,18.48)	(19.17, 20.58)	(12.17, 13.35)	(9.46,10.55)
	Hour 5	Average	(2.22,2.30)	(2.59,2.68)	(2.64,2.74)	(2.11,2.18)	(1.85,1.90)
		Max	(16.61,18.00)	(20.59,22.40)	(21.44, 23.02)	(15.31, 16.71)	(11.85, 13.07)
	Hour 6	Average	(2.32,2.41)	(2.64,2.75)	(2.69,2.81)	(2.23,2.32)	(1.89,1.96)
		Max	(16.31,17.72)	(18.71,20.37)	(19.78, 21.29)	(14.76, 16.05)	(10.77, 12.10)
	Hour 7	Average	(2.16,2.26)	(2.58,2.70)	(2.67,2.79)	(2.08,2.17)	(1.78,1.84)
		Max	(14.13,15.35)	(17.91,19.32)	(18.51, 19.89)	(13.37, 14.61)	(9.55, 10.64)
	Hour 8	Average	(1.91,1.98)	(2.52,2.63)	(2.69,2.81)	(1.86,1.93)	(1.69,1.75)
		Max	(12.70,14.11)	(17.74,19.25)	(19.33,20.78)	(11.44,12.66)	(8.74, 10.08)
	Hour 9	Average	(1.85,1.93)	(2.29,2.42)	(2.76,2.92)	(1.83,1.89)	(1.64,1.70)
		Max	(10.32,11.45)	(14.63,16.05)	(17.19, 18.53)	(9.80,10.83)	(7.12,8.11)
	Hour 10	Average	(1.87,1.97)	(2.12,2.25)	(2.60,2.75)	(1.76,1.86)	(1.61,1.69)
		Max	(7.65,8.70)	(10.13,11.46)	(13.26,14.57)	(6.83,7.87)	(4.92,5.61)
	Hour 11	Average	(1.74,1.90)	(1.73,1.89)	(2.02,2.41)	(1.72,1.88)	(1.77,1.96)
		Max	(1.99,2.20)	(2.06,2.30)	(2.57,3.07)	(1.99,2.21)	(1.98,2.24)

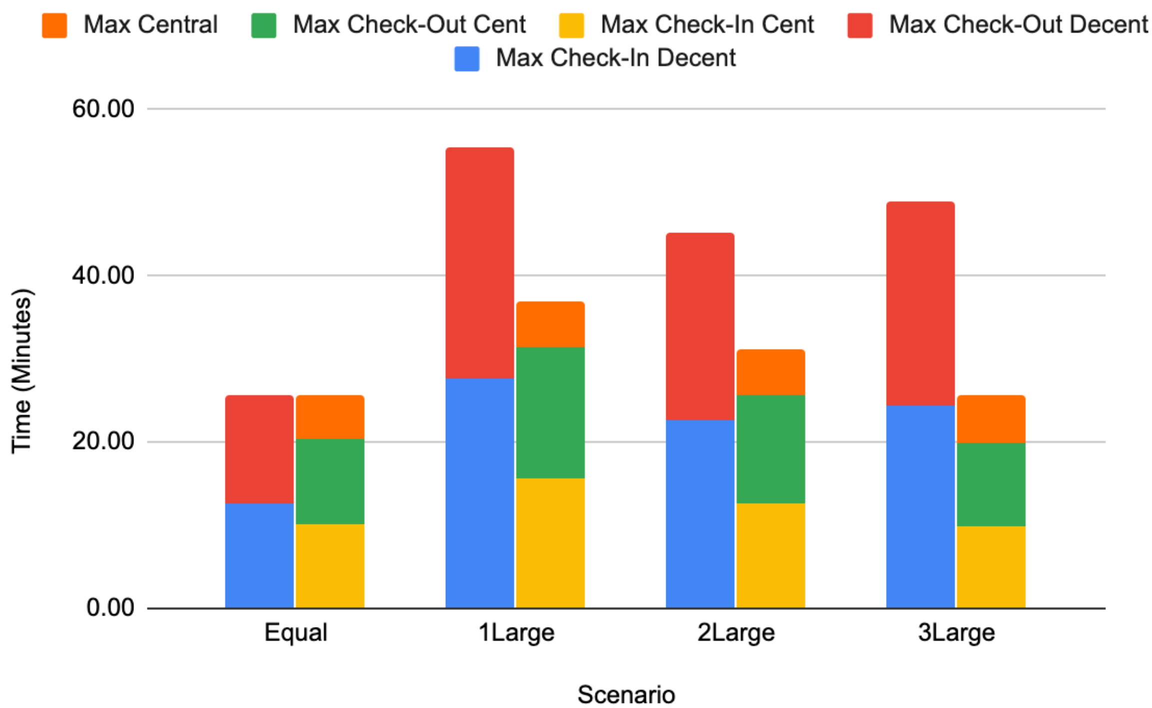

Figure A1: Maximum Times for Clinical Mixture Experiments

Table A10: Results of Clinic Mixture Experiments for the Decentralized Model

Decentralized	Setup	Metric	Scenario 1 Equal	Scenario 2 1 Large Clinic	Scenario 3 2 Large Clinics	Scenario 4 3 Large Clinics
Clinical Wait Time	Check In	Average	3.03	10.63	8.82	10.17
		Max	12.57	27.63	22.59	24.42
	Check Out	Average	3.33	13.63	11.14	13.31
		Max	13.00	27.80	22.68	24.66
Patient Wait Time	Hour 1	Average	1.62	1.13	1.13	1.29
		Max	3.43	2.89	2.60	3.10
	Hour 2	Average	1.80	2.71	1.56	1.67
		Max	10.16	11.52	10.58	14.56
	Hour 3	Average	2.51	16.17	6.68	5.04
		Max	23.64	73.91	42.44	45.20
	Hour 4	Average	3.67	6.11	20.72	16.82
		Max	35.65	56.98	93.98	76.95
	Hour 5	Average	5.74	2.69	18.19	36.17
		Max	48.22	18.04	89.62	110.39
	Hour 6	Average	6.61	2.67	16.63	36.94
		Max	52.20	18.00	44.40	120.56
	Hour 7	Average	6.09	2.49	16.88	20.64
		Max	50.32	15.60	41.39	90.84
	Hour 8	Average	5.62	2.30	16.22	8.26
		Max	48.42	14.43	40.05	48.72
	Hour 9	Average	4.51	2.23	13.19	3.30
		Max	38.78	11.45	33.31	16.85
	Hour 10	Average	2.99	2.01	7.32	1.88
		Max	18.34	6.65	20.21	6.39
	Hour 11	Average	1.97	1.68	2.77	1.22
		Max	2.64	1.82	3.31	1.39

Table A11: Results of Clinic Mixture Experiments for the Centralized Model

Centralized	Setup	Metric	Scenario 1 Equal	Scenario 2 1 Large Clinic	Scenario 3 2 Large Clinics	Scenario 4 3 Large Clinics
Clinical Wait Time	Check In	Average	1.06	5.01	3.79	2.13
		Max	10.14	15.61	12.73	9.87
	Check Out	Average	1.23	6.39	4.86	2.51
		Max	10.15	15.74	13.00	10.04
	Central	Average	0.69	0.72	0.67	0.72
		Max	5.41	5.69	5.36	5.66
Patient Wait Time	Hour 1	Average	1.52	1.13	1.09	1.20
		Max	2.98	2.80	2.41	2.43
	Hour 2	Average	1.58	1.21	1.19	1.25
		Max	5.67	6.26	6.52	5.49
	Hour 3	Average	1.83	2.43	1.90	1.66
		Max	13.58	21.09	3.70	15.68
	Hour 4	Average	2.31	10.89	5.87	3.93
		Max	21.17	51.48	43.42	27.27
	Hour 5	Average	2.98	32.37	17.44	9.62
		Max	27.41	96.54	61.16	39.56
	Hour 6	Average	3.32	33.59	29.30	14.24
		Max	28.42	108.48	74.37	47.70
	Hour 7	Average	3.13	11.23	33.64	15.92
		Max	27.51	64.51	81.01	50.04
	Hour 8	Average	2.81	2.72	32.06	13.22
		Max	24.56	18.26	79.68	44.70
	Hour 9	Average	2.57	2.07	23.26	10.06
		Max	19.92	10.13	65.56	37.17
	Hour 10	Average	2.39	2.02	11.93	7.55
		Max	13.16	6.79	37.72	28.22
	Hour 11	Average	1.95	1.73	3.76	3.61
		Max	2.09	2.26	2.92	2.09

Table A12: Confidence Intervals of Clinic Mixture Experiments for the Decentralized Model

Decentralized	Setup	Summary Metric	Scenario 1 Equal	Scenario 2 1 Large Clinic	Scenario 3 2 Large Clinics	Scenario 4 3 Large Clinics
Clinical Wait Time	Check In	Average	(2.82,3.24)	(11.93,13.21)	(3.10,3.56)	(12.36,13.64)
		Max	(10.52,10.74)	(27.23,28.03)	(13.49,13.78)	(27.39,28.20)
	Check Out	Average	(8.66,8.98)	(22.10,23.07)	(10.93,11.35)	(22.18,23.18)
		Max	(9.96,10.39)	(23.79,25.05)	(13.03,13.59)	(24.02,25.30)
Patient Wait Time	Hour 1	Average	(1.54,1.69)	(1.09,1.18)	(1.09,1.17)	(1.25,1.34)
		Max	(3.18,3.68)	(2.62,3.15)	(2.37,2.82)	(2.74,3.47)
	Hour 2	Average	(1.77,1.84)	(2.58,2.83)	(1.51,1.61)	(1.62,1.73)
		Max	(9.29,11.02)	(10.78,12.26)	(9.28,11.89)	(12.64,16.47)
	Hour 3	Average	(2.46,2.57)	(15.84,16.50)	(6.44,6.93)	(4.86,5.22)
		Max	(22.37,24.91)	(72.63,75.19)	(40.56,44.32)	(42.39,48.01)
	Hour 4	Average	(3.56,3.77)	(5.68,6.55)	(20.28,21.16)	(16.35,17.30)
		Max	(34.21,37.08)	(53.71,60.25)	(92.02,95.95)	(74.78,79.11)
	Hour 5	Average	(5.55,5.92)	(2.60,2.77)	(17.42,18.97)	(35.49,36.86)
		Max	(46.56,49.89)	(17.13,18.96)	(86.13,93.12)	(108.69,112.10)
	Hour 6	Average	(6.36,6.86)	(2.57,2.76)	(15.92,17.34)	(36.00,37.89)
		Max	(50.31,54.10)	(17.03,18.97)	(42.40,46.40)	(118.91,122.21)
	Hour 7	Average	(5.83,6.34)	(2.41,2.58)	(16.07,17.69)	(19.40,21.89)
		Max	(48.35,52.30)	(14.73,16.47)	(39.75,43.02)	(86.75,94.93)
	Hour 8	Average	(5.40,5.85)	(2.23,2.37)	(15.34,17.10)	(7.40,9.12)
		Max	(46.42,50.42)	(13.65,15.20)	(38.28,41.82)	(44.42,53.03)
	Hour 9	Average	(4.31,4.72)	(2.17,2.28)	(12.31,14.07)	(2.87,3.72)
		Max	(36.93,40.63)	(10.77,12.13)	(31.54,35.09)	(14.35,19.34)
	Hour 10	Average	(2.86,3.12)	(1.94,2.08)	(6.72,7.92)	(1.71,2.04)
		Max	(17.11,19.57)	(6.12,7.19)	(18.71,21.71)	(5.40,7.39)
	Hour 11	Average	(1.69,2.25)	(1.55,1.82)	(2.30,3.24)	(1.13,1.31)
		Max	(2.25,3.03)	(1.66,1.98)	(2.74,3.89)	(1.27,1.50)

Table A13: Confidence Intervals of Clinic Mixture Experiments for the Centralized Model

Centralized	Setup	Summary Metric	Scenario 1 Equal	Scenario 2 1 Large Clinic	Scenario 3 2 Large Clinics	Scenario 4 3 Large Clinics
Clinical Wait Time	Check In	Average	(0.88,1.24)	(9.40,10.87)	(1.03,1.43)	(9.41,10.89)
		Max	(4.88,5.13)	(15.03,16.19)	(6.24,6.55)	(15.15,16.33)
	Check Out	Average	(3.60,3.98)	(12.03,13.43)	(4.62,5.10)	(12.29,13.70)
		Max	(1.84,2.41)	(9.02,10.72)	(2.13,2.89)	(9.20,10.89)
Patient Wait Time	Hour 1	Average	(1.44,1.59)	(1.09,1.18)	(1.05,1.13)	(1.15,1.24)
		Max	(2.73,3.23)	(2.54,3.07)	(2.19,2.64)	(2.07,2.80)
	Hour 2	Average	(1.55,1.62)	(1.09,1.34)	(1.14,1.24)	(1.19,1.30)
		Max	(4.81,6.53)	(5.52,7.00)	(5.21,7.83)	(3.58,7.41)
	Hour 3	Average	(1.78,1.88)	(2.10,2.76)	(1.66,2.14)	(1.48,1.84)
		Max	(12.31,14.85)	(19.81,22.37)	(1.82,5.57)	(12.87,18.49)
	Hour 4	Average	(2.20,2.41)	(10.46,11.33)	(5.43,6.32)	(3.45,4.40)
		Max	(19.74,22.60)	(48.21,54.75)	(41.45,45.38)	(25.11,29.44)
	Hour 5	Average	(2.80,3.17)	(32.29,32.46)	(16.67,18.21)	(8.94,10.31)
		Max	(25.74,29.07)	(95.63,97.45)	(57.67,64.65)	(37.86,41.27)
	Hour 6	Average	(3.07,3.57)	(33.50,33.69)	(28.59,30.01)	(13.30,15.19)
		Max	(26.52,30.31)	(107.50,109.45)	(72.37,76.37)	(46.05,49.36)
	Hour 7	Average	(2.88,3.38)	(11.15,11.32)	(32.83,34.45)	(14.67,17.17)
		Max	(25.54,29.49)	(63.64,65.38)	(79.38,82.64)	(45.95,54.13)
	Hour 8	Average	(2.59,3.03)	(2.64,2.79)	(31.19,32.94)	(12.36,14.08)
		Max	(22.57,26.56)	(17.48,19.03)	(77.91,81.45)	(40.39,49.01)
	Hour 9	Average	(2.37,2.77)	(2.01,2.13)	(22.38,24.14)	(9.64,10.49)
		Max	(18.07,21.77)	(9.45,10.81)	(63.78,67.34)	(34.68,39.66)
	Hour 10	Average	(2.26,2.52)	(1.95,2.09)	(11.33,12.54)	(7.38,7.71)
		Max	(11.93,14.39)	(6.25,7.33)	(36.22,39.22)	(27.23,29.21)
	Hour 11	Average	(1.67,2.23)	(1.59,1.87)	(3.29,4.23)	(3.52,3.70)
		Max	(1.99,2.78)	(1.70,2.01)	(3.93,5.07)	(4.53,4.76)

Table A14: Results of Multiple Appointment Scenarios for Decentralized Model

Decentralized	Setup	Summary	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
		Percent	0%	10%	20%	30%	40%
Clinical Wait Time	Check In	Average	0.65	0.76	0.88	1.12	1.52
		Max	5.53	6.31	7.12	8.57	10.37
	Check Out	Average	0.70	0.81	0.95	1.21	1.67
		Max	5.85	6.63	7.60	8.89	10.74
Patient Wait Time	Hour 1	Average	2.07	2.05	1.97	2.03	2.11
		Max	3.05	3.16	3.10	3.72	4.53
	Hour 2	Average	1.63	1.67	1.71	1.80	2.02
		Max	5.16	6.28	7.18	9.01	13.52
	Hour 3	Average	1.66	1.73	1.81	1.95	2.23
		Max	8.88	11.09	12.87	15.97	21.35
	Hour 4	Average	2.04	2.13	2.26	2.39	2.75
		Max	14.05	15.84	17.77	20.76	25.67
	Hour 5	Average	2.32	2.42	2.60	2.80	3.37
		Max	17.26	18.42	20.17	23.67	29.34
	Hour 6	Average	2.30	2.42	2.66	2.98	3.78
		Max	16.63	17.77	19.06	22.99	28.85
	Hour 7	Average	1.98	2.13	2.34	2.77	3.71
		Max	13.25	14.83	16.83	20.23	28.85
	Hour 8	Average	1.83	1.99	2.12	2.47	3.28
		Max	11.84	14.50	15.90	19.34	26.02
	Hour 9	Average	1.66	1.73	1.88	2.06	2.76
		Max	9.05	9.71	15.90	13.11	18.50
	Hour 10	Average	1.62	1.65	1.69	1.94	2.26
		Max	5.97	6.33	6.34	8.06	10.27
	Hour 11	Average	1.87	1.82	1.95	1.94	2.30
		Max	2.14	2.07	2.30	2.23	2.74

Table A15: Results of Multiple Appointment Scenarios for Centralized Model

Centralized	Setup	Summary	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
		Percent	0%	10%	20%	30%	40%
Clinical Wait Time	Check In	Average	0.49	0.55	0.66	0.80	0.99
		Max	6.67	7.41	8.57	9.90	11.42
	Check Out	Average	0.59	0.66	0.78	0.95	1.16
		Max	6.99	7.72	8.82	10.04	11.45
	Central	Average	0.76	0.70	0.74	0.74	0.72
		Max	5.68	5.53	5.72	5.65	5.50
Patient Wait Time	Hour 1	Average	2.07	2.02	1.95	1.91	1.94
		Max	2.98	2.97	3.01	3.23	3.57
	Hour 2	Average	1.53	1.56	1.60	1.66	1.76
		Max	4.08	4.83	5.63	7.31	9.38
	Hour 3	Average	1.50	1.55	1.63	1.75	1.90
		Max	4.08	8.77	11.01	13.61	16.57
	Hour 4	Average	1.85	1.88	1.94	2.08	2.26
		Max	12.85	14.01	15.55	17.45	20.41
	Hour 5	Average	2.20	2.26	2.33	2.52	2.65
		Max	15.82	17.31	18.59	19.84	21.78
	Hour 6	Average	2.28	2.37	2.48	2.61	2.92
		Max	15.98	17.01	17.86	18.91	21.31
	Hour 7	Average	2.09	2.21	2.40	2.60	2.92
		Max	14.02	14.74	16.24	18.59	19.60
	Hour 8	Average	2.09	1.95	2.15	2.39	2.72
		Max	12.49	13.41	14.99	16.97	19.30
	Hour 9	Average	1.85	1.89	2.12	2.27	2.58
		Max	10.31	10.89	12.73	13.65	15.05
	Hour 10	Average	1.80	1.92	2.03	2.24	2.60
		Max	7.53	8.17	8.70	9.32	10.36
	Hour 11	Average	1.93	1.82	1.85	1.91	2.12
		Max	2.29	2.09	2.12	2.17	2.41

Table A16: Confidence Intervals of Multiple Appointment Scenarios for Decentralized Model

Decentralized	Setup	Summary	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
		Percent	0%	10%	20%	30%	40%
Clinical Wait Time	Check In	Average	(0.59,0.70)	(0.70,0.82)	(0.81,0.95)	(1.04,1.20)	(1.41,1.63)
		Max	(5.15,5.90)	(5.92,6.70)	(6.69,7.55)	(8.10,9.03)	(9.84,10.90)
	Check Out	Average	(0.64,0.76)	(0.74,0.88)	(0.87,1.02)	(1.12,1.30)	(1.54,1.79)
		Max	(5.46,6.25)	(6.22,7.05)	(7.16,8.03)	(8.41,9.36)	(10.21,11.28)
Patient Wait Time	Hour 1	Average	(2.05,2.10)	(2.02,2.08)	(1.94,2.00)	(1.99,2.08)	(2.04,2.18)
		Max	(3.00,3.10)	(3.06,3.25)	(2.99,3.20)	(3.52,3.93)	(4.12,4.93)
	Hour 2	Average	(1.61,1.65)	(1.65,1.69)	(1.69,1.73)	(1.78,1.83)	(1.98,2.06)
		Max	(4.92,5.39)	(5.93,6.63)	(6.76,7.60)	(8.44,9.57)	(12.67,14.37)
	Hour 3	Average	(1.64,1.69)	(1.71,1.75)	(1.79,1.83)	(1.93,1.98)	(2.19,2.27)
		Max	(8.46,9.31)	(10.54,11.65)	(12.19,13.56)	(15.23,16.70)	(20.30,22.39)
	Hour 4	Average	(2.01,2.08)	(2.09,2.17)	(2.22,2.30)	(2.34,2.43)	(2.70,2.81)
		Max	(13.47,14.63)	(15.18,16.51)	(17.05,18.48)	(19.94,21.59)	(24.63,26.70)
	Hour 5	Average	(2.27,2.37)	(2.37,2.47)	(2.54,2.66)	(2.75,2.86)	(3.29,3.46)
		Max	(16.54,17.98)	(17.68,19.16)	(19.24,21.09)	(22.79,24.55)	(28.29,30.39)
	Hour 6	Average	(2.25,2.36)	(2.35,2.49)	(2.58,2.73)	(2.89,3.06)	(3.66,3.89)
		Max	(15.81,17.46)	(16.91,18.63)	(18.09,20.02)	(22.07,23.91)	(27.71,29.99)
	Hour 7	Average	(1.92,2.03)	(2.08,2.18)	(2.28,2.40)	(2.69,2.85)	(3.59,3.84)
		Max	(12.41,14.10)	(14.06,15.61)	(15.98,17.67)	(19.32,21.13)	(27.70,30.00)
	Hour 8	Average	(1.80,1.87)	(1.95,2.04)	(2.07,2.17)	(2.42,2.53)	(3.17,3.40)
		Max	(11.03,12.65)	(13.73,15.27)	(15.05,16.74)	(18.46,20.23)	(24.87,27.16)
	Hour 9	Average	(1.64,1.69)	(1.70,1.76)	(1.84,1.92)	(2.02,2.11)	(2.66,2.87)
		Max	(8.49,9.61)	(9.12,10.30)	(15.21,16.59)	(12.35,13.87)	(17.54,19.46)
	Hour 10	Average	(1.58,1.65)	(1.61,1.69)	(1.66,1.73)	(1.89,2.00)	(2.17,2.34)
		Max	(5.53,6.41)	(5.83,6.83)	(5.86,6.81)	(7.49,8.62)	(9.49,11.05)
	Hour 11	Average	(1.74,2.00)	(1.73,1.92)	(1.77,2.13)	(1.81,2.08)	(2.08,2.53)
		Max	(2.01,2.28)	(1.96,2.18)	(2.02,2.58)	(2.06,2.40)	(2.43,3.05)

Table A17: Confidence Intervals of Multiple Appointment Scenarios for Centralized Model

Centralized	Setup	Summary	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
		Percent	0%	10%	20%	30%	40%
Clinical Wait Time	Check In	Average	(0.42,0.57)	(0.49,0.62)	(0.58,0.74)	(0.69,0.91)	(0.88,1.10)
		Max	(6.19,7.15)	(6.93,7.89)	(8.05,9.09)	(9.31,10.48)	(10.84,12.00)
	Check Out	Average	(0.54,0.65)	(0.61,0.71)	(0.71,0.85)	(0.85,1.06)	(1.06,1.27)
		Max	(6.50,7.47)	(7.22,8.22)	(8.29,9.34)	(9.45,10.63)	(10.86,12.04)
Patient Wait Time	Hour 1	Average	(2.05,2.09)	(2.00,2.04)	(1.93,1.98)	(1.88,1.95)	(1.90,1.98)
		Max	(2.94,3.01)	(2.92,3.01)	(2.94,3.07)	(3.08,3.38)	(3.37,3.77)
	Hour 2	Average	(1.52,1.55)	(1.55,1.57)	(1.58,1.61)	(1.64,1.69)	(1.73,1.78)
		Max	(3.99,4.17)	(4.58,5.07)	(5.30,5.95)	(6.71,7.91)	(8.87,9.88)
	Hour 3	Average	(1.48,1.51)	(1.54,1.56)	(1.61,1.65)	(1.72,1.77)	(1.88,1.92)
		Max	(3.71,4.45)	(8.24,9.29)	(10.42,11.61)	(12.93,14.29)	(15.94,17.20)
	Hour 4	Average	(1.82,1.87)	(1.85,1.90)	(1.92,1.97)	(2.05,2.12)	(2.23,2.29)
		Max	(12.20,13.50)	(13.37,14.65)	(14.86,16.23)	(16.71,18.19)	(19.67,21.15)
	Hour 5	Average	(2.16,2.24)	(2.22,2.30)	(2.29,2.38)	(2.46,2.57)	(2.60,2.71)
		Max	(15.16,16.48)	(16.61,18.00)	(17.86,19.31)	(19.14,20.54)	(21.08,22.48)
	Hour 6	Average	(2.23,2.32)	(2.32,2.41)	(2.43,2.53)	(2.53,2.69)	(2.84,2.99)
		Max	(15.29,16.67)	(16.31,17.72)	(17.19,18.54)	(18.14,19.67)	(20.52,22.11)
	Hour 7	Average	(2.04,2.13)	(2.16,2.26)	(2.34,2.45)	(2.52,2.69)	(2.84,2.99)
		Max	(13.36,14.69)	(14.13,15.35)	(15.60,16.88)	(17.89,19.29)	(18.86,20.34)
	Hour 8	Average	(2.05,2.12)	(1.91,1.98)	(2.11,2.20)	(2.32,2.46)	(2.64,2.79)
		Max	(11.86,13.12)	(12.70,14.11)	(14.35,15.63)	(16.27,17.67)	(18.53,20.06)
	Hour 9	Average	(1.81,1.88)	(1.85,1.93)	(2.07,2.17)	(2.18,2.35)	(2.50,2.66)
		Max	(9.82,10.80)	(10.32,11.45)	(12.18,13.28)	(12.92,14.38)	(14.32,15.77)
	Hour 10	Average	(1.76,1.84)	(1.87,1.97)	(1.97,2.09)	(2.13,2.34)	(2.51,2.69)
		Max	(7.03,8.03)	(7.65,8.70)	(8.15,9.25)	(8.61,10.02)	(9.71,11.01)
	Hour 11	Average	(1.84,2.01)	(1.74,1.90)	(1.71,2.00)	(1.78,2.04)	(1.96,2.29)
		Max	(2.18,2.40)	(1.99,2.20)	(1.95,2.28)	(2.02,2.33)	(2.15,2.66)

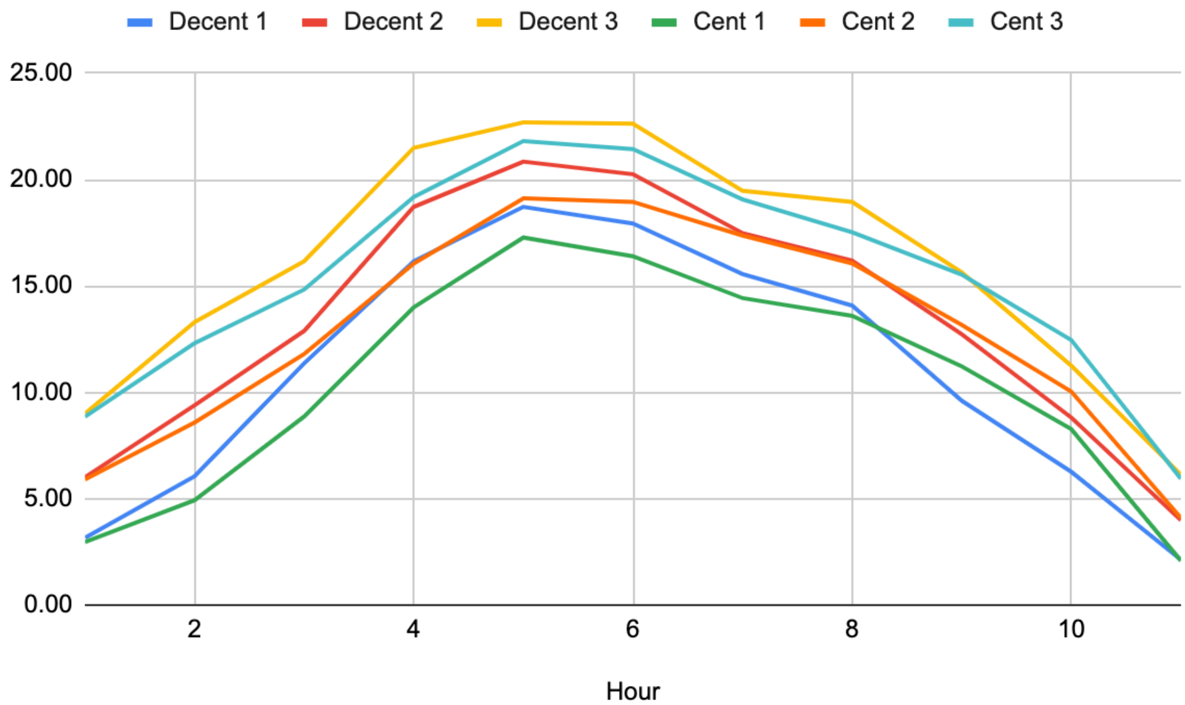

Figure A2: Maximum Patient Wait Times for Travel Time Experiments

Table A18: Results of Travel Time Experiments for the Decentralized Model

Decentralized	Setup		Scenario 1	Scenario 2	Scenario 3
		Metric	Average	Double	Triple
Patient Wait Time	Hour 1	Average	2.05	4.02	6.03
		Max	3.16	6.01	9.00
	Hour 2	Average	1.66	3.19	4.76
		Max	6.05	9.39	13.30
	Hour 3	Average	1.74	3.13	4.58
		Max	11.36	12.89	16.17
	Hour 4	Average	2.12	3.63	5.07
		Max	16.17	18.72	21.50
	Hour 5	Average	2.44	3.81	5.33
		Max	18.72	20.84	22.69
	Hour 6	Average	2.45	3.87	5.40
		Max	17.94	20.25	22.63
	Hour 7	Average	2.17	3.58	5.01
		Max	15.56	17.48	19.47
	Hour 8	Average	1.97	3.38	4.83
		Max	14.08	16.20	18.95
	Hour 9	Average	1.73	3.17	4.58
		Max	9.60	12.73	15.64
	Hour 10	Average	1.64	3.08	4.49
		Max	6.26	8.81	11.25
	Hour 11	Average	1.85	3.44	4.49
		Max	2.12	3.99	6.13

Table A19: Results of Travel Time Experiments for the Centralized Model

Decentralized	Setup		Scenario 1	Scenario 2	Scenario 3
		Metric	Average	Double	Triple
Patient Wait Time	Hour 1	Average	2.02	4.00	5.99
		Max	2.96	5.91	8.85
	Hour 2	Average	1.56	3.11	4.62
		Max	4.92	8.58	12.31
	Hour 3	Average	1.55	2.99	4.40
		Max	8.86	11.80	14.83
	Hour 4	Average	1.88	3.35	4.88
		Max	14.00	16.06	19.18
	Hour 5	Average	2.26	3.75	5.25
		Max	17.28	19.13	21.81
	Hour 6	Average	2.32	3.82	5.41
		Max	16.40	18.95	21.44
	Hour 7	Average	2.21	3.68	5.09
		Max	14.43	17.38	19.07
	Hour 8	Average	1.96	3.45	4.89
		Max	13.60	16.07	17.53
	Hour 9	Average	1.90	3.30	4.70
		Max	11.22	13.17	15.53
	Hour 10	Average	1.91	3.30	4.68
		Max	8.27	10.04	12.46
	Hour 11	Average	1.82	3.56	5.29
		Max	2.09	4.09	5.94

Table A20: Confidence Intervals of Travel Time Experiments for the Decentralized Model

Decentralized	Setup		Scenario 1	Scenario 2	Scenario 3
		Metric	Average	Double	Triple
Patient Wait Time	Hour 1	Average	(2.02,2.08)	(3.97,4.06)	(5.95,6.10)
		Max	(3.06,3.25)	(5.91,6.11)	(8.87,9.14)
	Hour 2	Average	(1.65,1.69)	(3.16,3.22)	(4.72,4.81)
		Max	(5.93,6.63)	(9.09,9.70)	(12.99,13.61)
	Hour 3	Average	(1.71,1.75)	(3.11,3.16)	(4.55,4.62)
		Max	(10.54,11.65)	(12.39,13.38)	(15.68,16.66)
	Hour 4	Average	(2.09,2.17)	(3.59,3.66)	(5.03,5.11)
		Max	(15.18,16.51)	(18.03,19.40)	(20.77,22.22)
	Hour 5	Average	(2.37,2.47)	(3.76,3.87)	(5.27,5.39)
		Max	(17.68,19.16)	(20.06,21.63)	(21.95,23.44)
	Hour 6	Average	(2.35,2.49)	(3.82,3.93)	(5.33,5.46)
		Max	(16.91,18.63)	(19.47,21.04)	(21.72,23.54)
	Hour 7	Average	(2.08,2.18)	(3.53,3.63)	(4.96,5.05)
		Max	(14.06,15.61)	(16.72,18.25)	(18.79,20.15)
	Hour 8	Average	(1.95,2.04)	(3.34,3.41)	(4.79,4.87)
		Max	(13.73,15.27)	(15.48,16.92)	(18.34,19.56)
	Hour 9	Average	(1.70,1.76)	(3.13,3.21)	(4.54,4.62)
		Max	(9.12,10.30)	(12.15,13.32)	(15.07,16.22)
	Hour 10	Average	(1.61,1.69)	(3.03,3.13)	(4.44,4.54)
		Max	(5.83,6.83)	(8.33,9.29)	(10.87,11.63)
	Hour 11	Average	(1.73,1.92)	(3.27,3.60)	(4.26,4.73)
		Max	(1.96,2.18)	(3.77,4.21)	(5.86,6.40)

Table A21: Confidence Intervals of Travel Time Experiments for the Centralized Model

Centralized	Setup		Scenario 1	Scenario 2	Scenario 3
		Metric	Average	Double	Triple
Patient Wait Time	Hour 1	Average	(2.00,2.04)	(3.95,4.05)	(5.92,6.06)
		Max	(2.92,3.01)	(5.83,5.98)	(8.74,8.97)
	Hour 2	Average	(1.55,1.57)	(3.08,3.13)	(4.59,4.66)
		Max	(4.58,5.07)	(8.34,8.82)	(12.04,12.59)
	Hour 3	Average	(1.54,1.56)	(2.97,3.01)	(4.38,4.42)
		Max	(8.24,9.29)	(11.34,12.26)	(14.36,15.31)
	Hour 4	Average	(1.85,1.90)	(3.32,3.38)	(4.85,4.91)
		Max	(13.37,14.65)	(15.43,16.69)	(18.54,19.83)
	Hour 5	Average	(2.22,2.30)	(3.71,3.78)	(5.20,5.29)
		Max	(16.61,18.00)	(18.44,19.81)	(21.10,22.53)
	Hour 6	Average	(2.32,2.41)	(3.78,3.87)	(5.35,5.46)
		Max	(16.31,17.72)	(18.20,19.70)	(20.72,22.16)
	Hour 7	Average	(2.16,2.26)	(3.63,3.72)	(5.04,5.14)
		Max	(14.13,15.35)	(16.72,18.03)	(18.44,19.70)
	Hour 8	Average	(1.91,1.98)	(3.42,3.49)	(4.85,4.93)
		Max	(12.70,14.11)	(15.41,16.72)	(16.97,18.08)
	Hour 9	Average	(1.85,1.93)	(3.26,3.34)	(4.66,4.74)
		Max	(10.32,11.45)	(12.64,13.71)	(15.03,16.03)
	Hour 10	Average	(1.87,1.97)	(3.25,3.35)	(4.61,4.74)
		Max	(7.65,8.70)	(9.59,10.48)	(12.01,12.90)
	Hour 11	Average	(1.74,1.90)	(3.35,3.78)	(5.04,5.54)
		Max	(1.99,2.20)	(3.86,4.33)	(5.65,6.23)

Table A22: Clinical Mixtures for Rerouting in Clinical Number Scenarios

4 Clinics		
Clinic Number	**Average Patients Per Day**	**Clinic Mixture**
1	27	15.00
2	55	30.56
3	33	18.33
4	65	36.11
8 Clinics		
Clinic Number	**Average Patients Per Day**	**Clinic Mixture**
1	27	6.14
2	55	12.50
3	33	7.50
4	65	14.77
5	63	14.32
6	61	13.86
7	85	19.32
8	51	11.59
12 Clinics		
Clinic Number	**Average Patients Per Day**	**Clinic Mixture**
1	27	3.87
2	55	7.89
3	33	4.73
4	65	9.33
5	63	9.04
6	61	8.75
7	85	12.20
8	51	7.32
9	66	9.47
10	39	5.60
11	116	16.64
12	36	5.16
16 Clinics		
Clinic Number	**Average Patients Per Day**	**Clinic Mixture**
1	27	3.47
2	55	7.06
3	33	4.24
4	65	8.34
5	63	8.09
6	61	7.83
7	85	10.91
8	51	6.55
9	66	8.47
10	39	5.01

11	116	14.89
12	36	4.62
13	17	2.18
14	24	3.08
15	21	2.70
16	20	2.57
20 Clinics		
Clinic Number	**Average Patients Per Day**	**Clinic Mixture**
1	27	2.77
2	55	5.64
3	33	3.38
4	65	6.67
5	63	6.46
6	61	6.26
7	85	8.72
8	51	5.23
9	66	6.77
10	39	4.00
11	116	11.90
12	36	3.69
13	17	1.74
14	24	2.46
15	21	2.15
16	20	2.05
17	49	5.03
18	49	5.03
19	49	5.03
20	49	5.03

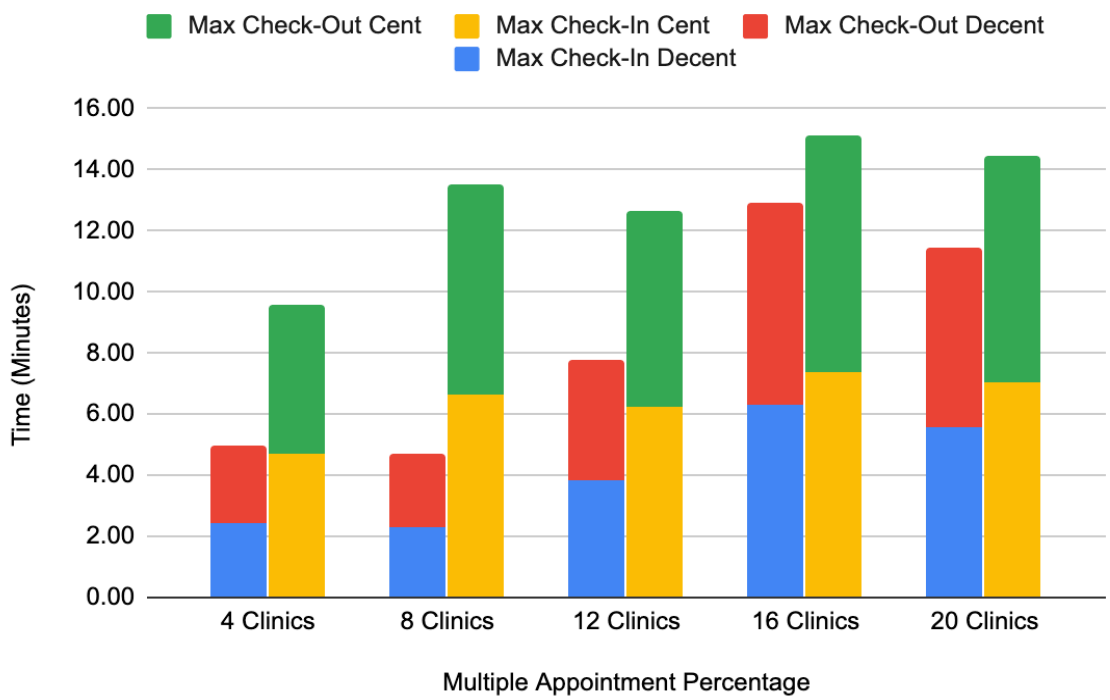

Figure A3: Maximum Clinic Wait Times for Clinic Number Experiments

Table A23: Results of Clinic Number Experiments for the Decentralized Model

Decentralized	Setup	Summary	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
		Arrival Rate Table	4 Clinics	8 Clinics	12 Clinics	16 Clinics	20 Clinics
Clinical Wait Time	Check In	Average	0.14	0.21	0.29	0.76	0.63
		Max	2.42	2.28	3.81	6.31	5.56
	Check Out	Average	0.14	0.22	0.30	0.81	0.69
		Max	2.53	2.41	3.97	6.63	5.92
Patient Wait Time	Hour 1	Average	1.47	1.46	2.03	2.05	1.97
		Max	1.68	1.67	2.97	3.16	3.15
	Hour 2	Average	0.92	1.06	1.56	1.67	1.79
		Max	2.12	2.40	4.61	6.28	6.39
	Hour 3	Average	0.91	1.18	1.57	1.73	1.80
		Max	3.00	3.75	7.62	11.09	11.31
	Hour 4	Average	0.96	1.24	1.81	2.13	2.14
		Max	3.50	4.45	9.87	15.84	16.17
	Hour 5	Average	1.03	1.35	2.01	2.42	2.37
		Max	3.68	5.45	11.19	18.42	19.10
	Hour 6	Average	1.06	1.26	2.06	2.42	2.42
		Max	3.57	4.67	10.64	17.77	18.36
	Hour 7	Average	1.00	1.26	1.91	2.13	2.16
		Max	3.23	4.40	9.86	14.83	15.46
	Hour 8	Average	0.94	1.25	1.66	1.99	2.02
		Max	2.87	4.04	8.01	14.50	14.09
	Hour 9	Average	0.85	1.23	1.53	1.73	1.80
		Max	2.03	3.39	5.91	9.71	10.48
	Hour 10	Average	0.78	1.21	1.48	1.65	1.72
		Max	1.41	2.57	3.95	6.33	7.04
	Hour 11	Average	0.86	1.26	1.80	1.82	1.89
		Max	0.87	1.33	2.07	2.07	2.27

Table A24: Results of Clinic Number Experiments for the Centralized Model

Centralized	Setup	Summary	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
		Arrival Rate Table	4 Clinics	8 Clinics	12 Clinics	16 Clinics	20 Clinics
Clinical Wait Time	Check In	Average	0.26	0.39	0.36	0.55	0.50
		Max	4.73	6.68	6.26	7.41	7.07
	Check Out	Average	0.31	0.48	0.43	0.66	0.61
		Max	4.88	6.83	6.41	7.72	7.40
	Central	Average	0.00	0.03	0.29	0.70	1.22
		Max	0.05	1.40	3.54	5.53	7.38
Patient Wait Time	Hour 1	Average	1.49	1.46	2.02	2.02	1.96
		Max	1.71	1.68	2.94	2.97	3.04
	Hour 2	Average	0.92	1.07	1.49	1.56	1.71
		Max	2.15	2.56	3.75	4.83	5.36
	Hour 3	Average	0.89	1.22	1.48	1.55	1.67
		Max	2.84	5.39	6.63	8.77	9.03
	Hour 4	Average	1.08	1.47	1.72	1.88	1.97
		Max	4.84	8.83	10.43	14.01	14.39
	Hour 5	Average	1.37	1.96	2.06	2.26	2.31
		Max	6.26	12.25	12.99	17.31	18.00
	Hour 6	Average	1.51	1.91	2.14	2.37	2.38
		Max	6.52	11.45	12.76	17.01	16.94
	Hour 7	Average	1.34	1.81	2.03	2.21	2.27
		Max	5.54	10.51	11.68	14.74	15.64
	Hour 8	Average	1.22	1.61	1.78	1.95	2.07
		Max	4.91	8.78	10.21	13.41	14.13
	Hour 9	Average	1.10	1.67	1.82	1.89	1.95
		Max	3.60	7.95	9.31	10.89	10.96
	Hour 10	Average	1.03	1.58	1.78	1.92	1.88
		Max	2.14	5.28	6.50	8.17	7.84
	Hour 11	Average	0.84	1.45	1.81	1.82	1.82
		Max	0.86	1.58	2.07	2.09	2.21

Table A25: Confidence Intervals of Clinic Number Experiments for the Decentralized Model

Decentralized	Setup	Summary	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
		Arrival Rate Table	4 Clinics	8 Clinics	12 Clinics	16 Clinics	20 Clinics
Clinical Wait Time	Check In	Average	(0.12,0.15)	(0.20,0.23)	(0.26,0.32)	(0.70,0.82)	(0.58,0.69)
		Max	(2.20,2.63)	(2.08,2.47)	(3.56,4.07)	(5.92,6.70)	(5.19,5.93)
	Check Out	Average	(0.13,0.16)	(0.20,0.23)	(0.27,0.33)	(0.74,0.88)	(0.63,0.75)
		Max	(2.30,2.75)	(2.21,2.62)	(3.71,4.23)	(6.22,7.05)	(5.54,6.30)
Patient Wait Time	Hour 1	Average	(1.44,1.50)	(1.43,1.50)	(2.00,2.05)	(2.02,2.08)	(1.95,1.99)
		Max	(1.64,1.72)	(1.63,1.72)	(2.91,3.03)	(3.06,3.25)	(3.02,3.28)
	Hour 2	Average	(0.90,0.94)	(1.05,1.07)	(1.54,1.58)	(1.65,1.69)	(1.78,1.81)
		Max	(2.04,2.19)	(2.32,2.49)	(4.39,4.82)	(5.93,6.63)	(6.10,6.68)
	Hour 3	Average	(0.89,0.92)	(1.17,1.18)	(1.55,1.59)	(1.71,1.75)	(1.79,1.82)
		Max	(2.82,3.18)	(3.59,3.90)	(7.27,7.97)	(10.54,11.65)	(10.76,11.85)
	Hour 4	Average	(0.94,0.97)	(1.23,1.25)	(1.77,1.84)	(2.09,2.17)	(2.11,2.17)
		Max	(3.26,3.74)	(4.25,4.65)	(9.46,10.28)	(15.18,16.51)	(15.36,16.99)
	Hour 5	Average	(1.00,1.05)	(1.33,1.36)	(1.97,2.06)	(2.37,2.47)	(2.33,2.41)
		Max	(3.45,3.91)	(5.19,5.72)	(10.72,11.66)	(17.68,19.16)	(18.24,19.96)
	Hour 6	Average	(1.03,1.09)	(1.24,1.28)	(1.99,2.12)	(2.35,2.49)	(2.36,2.47)
		Max	(3.32,3.82)	(4.44,4.90)	(10.15,11.13)	(16.91,18.63)	(17.44,19.28)
	Hour 7	Average	(0.97,1.02)	(1.24,1.28)	(1.86,1.96)	(2.08,2.18)	(2.12,2.20)
		Max	(3.01,3.46)	(4.15,4.64)	(9.41,10.30)	(14.06,15.61)	(14.66,16.25)
	Hour 8	Average	(0.92,0.96)	(1.24,1.26)	(1.63,1.69)	(1.95,2.04)	(1.99,2.05)
		Max	(2.68,3.06)	(3.84,4.24)	(7.65,8.37)	(13.73,15.27)	(13.37,14.81)
	Hour 9	Average	(0.83,0.87)	(1.22,1.24)	(1.51,1.55)	(1.70,1.76)	(1.77,1.83)
		Max	(1.93,2.14)	(3.25,3.52)	(5.65,6.18)	(9.12,10.30)	(9.87,11.10)
	Hour 10	Average	(0.75,0.82)	(1.20,1.23)	(1.46,1.50)	(1.61,1.69)	(1.68,1.75)
		Max	(1.31,1.52)	(2.50,2.65)	(3.76,4.14)	(5.83,6.83)	(6.53,7.55)
	Hour 11	Average	(0.70,1.02)	(1.17,1.36)	(1.72,1.87)	(1.73,1.92)	(1.80,1.99)
		Max	(0.71,1.03)	(1.23,1.43)	(1.98,2.16)	(1.96,2.18)	(2.15,2.39)

Table A26: Confidence Intervals of Clinic Number Experiments for the Centralized Model

Centralized	Setup	Summary	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
		Arrival Rate Table	4 Clinics	8 Clinics	12 Clinics	16 Clinics	20 Clinics
Clinical Wait Time	Check In	Average	(0.23,0.29)	(0.35,0.43)	(0.32,0.39)	(0.49,0.62)	(0.45,0.54)
		Max	(4.37,5.09)	(6.24,7.11)	(5.86,6.65)	(6.93,7.89)	(6.59,7.55)
	Check Out	Average	(0.27,0.34)	(0.43,0.52)	(0.39,0.47)	(0.61,0.71)	(0.55,0.67)
		Max	(4.53,5.22)	(6.40,7.26)	(6.02,6.81)	(7.22,8.22)	(6.91,7.89)
	Central	Average	(1.46,1.52)	(1.43,1.50)	(2.00,2.04)	(2.00,2.04)	(1.94,1.98)
		Max	(1.67,1.75)	(1.64,1.73)	(2.89,2.99)	(2.92,3.01)	(2.94,3.14)
Patient Wait Time	Hour 1	Average	(0.90,0.94)	(1.05,1.08)	(1.48,1.50)	(1.55,1.57)	(1.70,1.72)
		Max	(2.02,2.27)	(2.41,2.70)	(3.60,3.90)	(4.58,5.07)	(5.16,5.56)
	Hour 2	Average	(0.87,0.90)	(1.20,1.23)	(1.46,1.49)	(1.54,1.56)	(1.66,1.68)
		Max	(2.64,3.04)	(5.04,5.73)	(6.28,6.98)	(8.24,9.29)	(8.54,9.51)
	Hour 3	Average	(1.04,1.12)	(1.44,1.49)	(1.70,1.74)	(1.85,1.90)	(1.95,1.99)
		Max	(4.47,5.20)	(8.37,9.28)	(9.97,10.89)	(13.37,14.65)	(13.82,14.97)
	Hour 4	Average	(1.31,1.43)	(1.90,2.01)	(2.02,2.10)	(2.22,2.30)	(2.27,2.34)
		Max	(5.86,6.66)	(11.75,12.75)	(12.51,13.48)	(16.61,18.00)	(17.33,18.67)
	Hour 5	Average	(1.43,1.60)	(1.86,1.97)	(2.09,2.19)	(2.32,2.41)	(2.34,2.42)
		Max	(6.09,6.95)	(10.92,11.99)	(12.24,13.28)	(16.31,17.72)	(16.25,17.63)
	Hour 6	Average	(1.28,1.40)	(1.76,1.87)	(1.99,2.07)	(2.16,2.26)	(2.24,2.31)
		Max	(5.16,5.92)	(9.99,11.03)	(11.20,12.16)	(14.13,15.35)	(15.00,16.28)
	Hour 7	Average	(1.16,1.27)	(1.57,1.65)	(1.75,1.81)	(1.91,1.98)	(2.04,2.10)
		Max	(4.54,5.29)	(8.31,9.24)	(9.76,10.66)	(12.70,14.11)	(13.51,14.74)
	Hour 8	Average	(1.05,1.15)	(1.62,1.72)	(1.78,1.87)	(1.85,1.93)	(1.92,1.98)
		Max	(3.29,3.90)	(7.50,8.40)	(8.86,9.76)	(10.32,11.45)	(10.49,11.42)
	Hour 9	Average	(0.95,1.11)	(1.53,1.64)	(1.73,1.84)	(1.87,1.97)	(1.83,1.92)
		Max	(1.91,2.38)	(4.90,5.67)	(6.07,6.93)	(7.65,8.70)	(7.38,8.29)
	Hour 10	Average	(0.69,0.99)	(1.25,1.65)	(1.72,1.90)	(1.74,1.90)	(1.74,1.91)
		Max	(0.71,1.02)	(1.33,1.83)	(1.95,2.18)	(1.99,2.20)	(2.08,2.35)
	Hour 11	Average	(0.23,0.29)	(0.35,0.43)	(0.32,0.39)	(0.49,0.62)	(0.45,0.54)
		Max	(4.37,5.09)	(6.24,7.11)	(5.86,6.65)	(6.93,7.89)	(6.59,7.55)

A.4 Results and Confidence Intervals of General Experiments

Tables A27 and A28 show both the results and confidence intervals of the validation experiment run.

Table A27: Results of Decentralized Validation Model

Decentralized		Results	Confidence Intervals
Check In	Average	0.77	(0.70,0.83)
	Max	6.38	(5.98,6.77)
Check Out	Average	0.83	(0.76,0.90)
	Max	6.75	(6.34,7.17)
Hour 1	Average	2.05	(0.74,0.79)
	Max	3.16	(6.28,6.47)
Hour 2	Average	1.66	(0.81,0.85)
	Max	6.05	(6.40,7.10)
Hour 3	Average	1.74	(2.02,2.07)
	Max	11.36	(2.61,3.72)
Hour 4	Average	2.12	(1.62,1.69)
	Max	16.17	(5.39,6.72)
Hour 5	Average	2.44	(1.69,1.79)
	Max	18.72	(10.62,12.10)
Hour 6	Average	2.45	(2.05,2.19)
	Max	17.94	(15.31,17.03)
Hour 7	Average	2.17	(2.39,2.50)
	Max	15.56	(17.94,19.50)
Hour 8	Average	1.97	(2.41,2.49)
	Max	14.08	(17.17,18.71)
Hour 9	Average	1.73	(2.14,2.21)
	Max	9.60	(14.97,16.15)
Hour 10	Average	1.64	(1.93,2.00)
	Max	6.26	(13.58,14.58)
Hour 11	Average	1.85	(1.63,1.83)
	Max	2.12	(9.49,9.71)

Table A28: Results of Centralized Validation Model

Centralized		Results	Confidence Intervals
Check In	Average	0.55	(0.49,0.61)
	Max	7.42	(6.94,7.90)
Check Out	Average	0.66	(0.61,0.71)
	Max	7.72	(7.22,8.22)
Central	Average	0.69	Excluded
	Max	5.49	Excluded
Hour 1	Average	2.02	(0.53,0.57)
	Max	2.96	(7.38,7.46)
Hour 2	Average	1.56	(0.65,0.67)
	Max	4.92	(7.47,7.96)
Hour 3	Average	1.55	(0.68,0.70)
	Max	8.86	(4.96,6.01)
Hour 4	Average	1.88	(1.99,2.04)
	Max	14.00	(2.32,3.60)
Hour 5	Average	2.26	(1.53,1.60)
	Max	17.28	(4.23,5.62)
Hour 6	Average	2.32	(1.50,1.59)
	Max	16.40	(8.16,9.57)
Hour 7	Average	2.21	(1.83,1.92)
	Max	14.43	(13.39,14.61)
Hour 8	Average	1.96	(2.23,2.30)
	Max	13.60	(16.57,17.99)
Hour 9	Average	1.90	(2.28,2.36)
	Max	11.22	(15.83,16.96)
Hour 10	Average	1.91	(2.16,2.26)
	Max	8.27	(13.91,14.96)
Hour 11	Average	1.82	(1.87,2.04)
	Max	2.09	(13.49,13.70)